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Visual Object Classification Using Computer Vision Techniques

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Dedication

This work is dedicated to.

My wonderful parents, without whom I would not be able to accomplish this work Thank you very much and may God bless them.

To my husband and my daughter, who have been tremendously supportive of me via their patience and prayers may God bless them.

To my two brothers, who have been tremendously supportive of me may God bless them

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Abstract

Due to the increasing importance of agriculture as a sector in general and the role of plants in human life in particular, humans have placed a high value on it as an object. Plants are affected by a variety of diseases, which can severely diminish their yield or even eliminate them out in some situations, posing a huge danger to world food security. It is critical to discover this disaster early to satisfy the increasing demands of an expanding population. Plants have a tremendous impact on human life, whether in the environmental sector (such as oxygen and water) or in the industrial sector (such as medicine and cosmetics). Classification errors can result in significant costs and losses, particularly in key domains such as medicine, where toxic species are mistakenly categorized as medicinal plants. Traditional plant classification of species or diseases can be established by looking at features such as shape, texture, and many others. However, identifying plant species or diseases from field observations can be difficult, time-consuming, and requires specialized knowledge. Computer vision techniques can be useful for identifying species or diseases. Several practical challenges are presented, such as significant intra-variability, the presence of shadows in sunny settings, inter-similarity, and unexpected changes in camera parameters. Several of these difficulties are addressed in this thesis. Several contributions have been proposed to address the two mentioned problems. In the first one, we examined the present state of research on computer vision approaches for plant identification. The investigated methods' weaknesses and inadequacies were found, opening the door to new challenges and real difficulties. In the second, given that plant leaves are characterized by shape and veins, we have proposed a fully automatic method for plant identification based on shape and texture features. Because leaf contour is sufficiently informative to define botanical character parts, in the third contribution, we have proposed a modified shape feature. In the fourth, fifth, and sixth contribution, as regards to the literature, the performance of classifiers has no superiority among them. In order to gather from their advantages and improve the recognition rates, we have dealt with several combination methods, parallel and serial. Recently, deep learning has revolutionized the field of machine learning and image classification, which has led us to deal with it for plant classification by proposing it as a novel classifier for plant leaf classification and as feature extraction for plant disease. The auto-encoder and Siamese neural network architecture has been used as novel classifier, and we adopted a hierarchical technique to solve the inter-species problem. The experimental findings demonstrate the efficacy of our contributions in comparison to the state of the art. The results of this thesis show that there is significant improvement in both plant recognition and plant disease by using novel machine learning and deep learning methods.

Keywords: plant leaf classification, plant leaf diseases, feature extraction, classifier combination, deep learning, hierarchical classification.

Résumé

Compte tenu de l'importance croissante de l'agriculture en tant que secteur en général, et du rôle des plantes dans la vie humaine en particulier, les humains lui ont accordé une grande valeur en tant qu'objet. Les plantes sont affectées par une variété de maladies, qui peuvent gravement diminuer leur rendement ou même l'anéantir dans certaines situations, ce qui constitue un énorme danger pour la sécurité alimentaire mondiale. Il est essentiel de découvrir cette catastrophe tôt pour satisfaire les demandes croissantes d'une population en expansion. Les plantes ont un impact énorme sur la vie humaine, que ce soit dans le secteur environnemental (comme l'oxygène et l'eau) ou dans le secteur industriel (comme la médecine et les produits cosmétiques). Les erreurs de classification peuvent entraîner des coûts et des pertes importants, en particulier dans des domaines clés tels que la médecine, où les espèces toxiques sont classées par erreur dans la catégorie des plantes médicinales. La classification traditionnelle des espèces ou des maladies de plantes peut être établie en examinant des caractéristiques telles que la forme, la texture et bien d'autres. Cependant, l'identification d'espèces végétales ou de maladies à partir d'observations sur le terrain peut être difficile, longue et nécessite des connaissances spécialisées. Les techniques de vision par ordinateur peuvent être utiles pour identifier les espèces ou les maladies. Plusieurs défis pratiques sont présentés, tels qu'une intra-variabilité significative, la présence d'ombres dans des environnements ensoleillés, une inter-similarité et des changements inattendus dans les paramètres de la caméra. Plusieurs de ces difficultés sont abordées dans cette thèse. Pour solutioner les deux problematic mentionné nous avons proposé plusieurs contributions dans la première nous avons examiné l'état actuel de la recherche sur les approches de vision par ordinateur pour l'identification des plantes, les faiblesses et les insuffisances des méthodes étudiées, ouvrant la porte à de nouveaux défis et de réelles difficultés. Dans la seconde, comme la feuille de la plante étant caractérisée par sa forme et ses nervures, nous avons proposé une méthode entièrement automatique pour l'identification des plantes basée sur les caractéristiques de forme et de texture. Parce que le contour de la feuille est suffisamment informatif pour définir les parties des caractères botaniques, dans la troisième contribution, nous avons proposé une caractéristique de forme modifiée. Dans la quatrième, cinquième et sixième en ce qui concerne la littérature, la performance des classificateurs n'a aucune supériorité parmi eux, afin de tirer parti de leurs avantages et d'améliorer les taux de reconnaissance, nous avons traités plusieurs méthodes de combinaison parallèle et sérielle. Récemment, l'apprentissage en profondeur a révolutionné le domaine de l'apprentissage automatique et de la classification d'images, ça nous a conduit à l'aborder pour la classification des plantes en le proposant comme un nouveau classificateur pour la classification des feuilles de plantes et comme extraction de caractéristiques pour les maladies de plantes. L'auto-encodeur et le Siamese a été utilisée comme nouveau classificateur, pour surmonter le problème inter-espèces nous avons exploité une stratégie hiérarchique. Les résultats expérimentaux démontrent l'efficacité de nos contributions par rapport à l'état de l'art. Les résultats de cette thèse montrent qu'il y a une amélioration significative à la fois de la reconnaissance des plantes et des maladies des plantes en utilisant de nouvelles méthodes d'apprentissage automatique et d'apprentissage en profondeur.

Mots-clés : classification des feuilles de plantes, classification des maladies des feuilles de plantes, extraction de characteristique, combinaison de classificateurs, apprentissage profond, classification hiérarchique.

ملخص

نظرًا للأهمية المتزايدة للزراعة كقطاع بشكل عام، ودور النباتات في حياة الإنسان بشكل خاص، فقد اهتم بها البشربشكل كبير. تتأثر النباتات بمجموعة متنوعة من الأمراض، والتي يمكن أن تقلل بشدة من المحصول أو حتى تقضي عليه في بعض الحالات، مما يشكل خطرًا كبيرًا على الأمن الغذائي العالمي. فبات من الأهمية بمكان اكتشاف وتفادي هذه الكارثة مبكرًا لتلبية الطلبات المتزايدة لعدد السكان المتزايد. للنباتات تأثير هائل على حياة الإنسان، سواء في القطاع البيئي (مثل الأكسجين والماء) أو في القطاع الصناعي (مثل الأدوية ومستحضرات التجميل). يمكن أن تؤدي أخطاء التصنيف إلى تكاليف وخسائر كبيرة، لا سيما في المجالات الحساسة مثل الطب، حيث يتم تصنيف الأنواع السامة عن طريق الخطأ على أنها نباتات طبية. تقليديا يمكن تصنيف أنواع أو أمراض النبات من خلال النظر إلى ميزات مثل الشكل والنسيج والعديد من الميزات الأخرى. ومع ذلك، قد يكون تحديد أنواع النباتات أو الأمراض من الملاحظات الميدانية أمرًا صعبًا ويستغرق وقتًا طويلاً ويتطلب معرفة متخصصة. يمكن أن تكون تقنيات الرؤية الحاسوبية مفيدة في التعرف على الأنواع أو الأمراض. خلال التعرف العديد من التحديات العملية تواجهنا مثل التباين الداخلي الكبير، ووجود الظلال في الأماكن المشمسة، التشابه الخارجي، والتغيرات الغير المتوقعة في معلمات الكاميرا. العديد من هذه الصعوبات تمت معالجتها في هذه الأطروحة. لحل المشكلتين المذكورتين اعلاه اقترحنا العديد من المساهمات في الجزء الأول قمنا بدراسة مختلف تقنيات رؤية الكمبيوتر المستعملة لتحديد النباتات، بناءا على نقاط الضعف والقصور في الطرق التي تمت دراستها، تم فتح الباب أمام تحديات وصعوبات جديدة وحقيقية. في الجزء الثاني، بما ان أوراق النبات تتميز بالشكل والأوردة، اقترحنا طريقة أتوماتيكية لتحديد النبات بناءً على ميزات الشكل والنسيج. نظرًا لأن محيط الورقة مفيد بشكل كافٍ لتصنيف النبات، فقد اقترحنا في المساهمة الثالثة طريقة معدلة والتي تعتمد على استخراج خصائص الشكل من اجزاء مفتاحية للورقة. في الجزء الرابع والخامس والسادس وبناءا على ما تم تناوله في الدراسات السابقة، في انه لا يوجد تفوق على أداء المصنفات فيما بينها، ومن أجل الاستفادة من مزاياها وتحسين معدلات التعرف تعاملنا معها بعدة طرق تجميع منها المتوازية ومنها المتسلسلة. أحدث التعلم العميق مؤخرًا ثورة في مجال التعلم الآلي وتصنيف الصور، وهذا دفعنا إلى استعماله لتصنيف النباتات وذلك من خلال اقتراحه كمصنف جديد لتصنيف أوراق النبات وكاداة لاستخراج الخصائص بالنسبة لأمراض النبات. تم استخدام بنية الشبكة Siamese وauto-encoder كمصنف جديد. للتغلب على مشكلة التشابه الخارجي بين الأنواع استعملنا الاستراتيجية الهرمية. تظهر النتائج التجريبية فعالية مساهماتنا مقارنة بأحدث ما توصلت إليه التكنولوجيا. تظهر نتائج هذه الرسالة أن هناك تحسنًا ملحوظًا في كل من التعرف على النبات وأمراض النبات باستخدام التعلم الآلي المبتكر وأساليب التعلم العميق.

الكلمات المفتاحية: تصنيف أوراق النبات، أمراض أوراق النبات، استخراج الميزات، مجموعة المصنفات، التعلم العميق، التصنيف الهرمي.

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Published Journal Papers

- Hamrouni lamis, Oussama Aiadi, Belal Khaldi, Mohammed Lamine Kherfi .Plants species identification using computer vision techniques. Revue des bioressources, 7 (1), 8-8. 2017. Ouargla.
- Lamis Hamrouni, Mohammed Lamine Kherfi, Oussama Aiadi, Abdellah benbelghit. Plant Leaves Recognition Based on a Hierarchical One-Class Learning Scheme with Convolutional Auto-Encoder and Siamese Neural Network. Symmetry 13 (9) 1705, 2021. **IF:2.71.**

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- Lamis Hamrouni, Mohammed Lamine Kherfi. A Study on Machine Learning Techniques In Plant leaf Identification.
- Lamis Hamrouni, Mohammed Lamine Kherfi, Oussama Aiadi, Belal Khaldi. A Comparative study of multiple parallel combination schemes for automatic plant leaves recognition.
- Lamis Hamrouni, Mohammed Lamine Kherfi. Plant Leaves Classification Using A Modified Triangular Centroid Distance Matrix.
- Lamis Hamrouni, Mohammed Lamine Kherfi, Oussama Aiadi, Saad Eddine Cherra. Convolutional auto-encoder- for plant diseases recognition.

List of Abbreviations

ACD	Angle Contour Distance
ANN	Artificial Neural Network
AUC	Area Under Curve
AV	Average
CAE	Convolutional Auto Encoder
CCD	Centroid-ContourDescriptor
CCG	Centroid Contour Gradient
CNN	Convolutional Neural Network
CSS	Curvature Scale Space
CV	Computer Vision
DCGAN	Deep Convolutional Generative Adversarial Network
DDLA	Dual Deep Learning Architecture
DL	Deep Learning
DNA	Deoxyribose Nucleic Acid
DP	Dynamic Programming
EDH	Edge Direction Histogram
EH	Edge Histogram
ELM	Extreme Learning Machine
EM	Expectation Maximization
FC	Fully Connected layer
FD	Fourier Descriptor
FPR	False Positive Rate
FSL	Few-Shot Learning
GAC	Guided Active Contour
GLCM	Grey Level Co-occurrence Matrix
HMMD	Hue-Max-Min-Diff
HSI	Hue Saturation Intensity
HSV	Hue Saturation Value

KNN	K-Nearest Neighbors
ICL	Institute of Intelligent Machines
IDSC	Inner Distance Shape Context
LBP	Local Binary Patterns
LDA	Linear Discriminant Analysis
LR	Logistic Regression
MARCH	Multiscale-Arch-Height
MAX	Maximum
MCC	Multiscale Convexity/Concavity
MCHC	Moving Center Hypersphere Classifier
MCS	Multiple Classifier System
MDM	Multiscale Distance Matrix
MIN	Minimum
MLP	Multi Layer Perceptron
MMTCD	Modified Multiscale Triangular Centroid Distance
MTCD	Multiscale Triangular Centroid Distance
MSF	Multi-Scale Fusion
NB	Naïve Bayes
NM	Novel Method
PCA	Principal Component Analysis
PHOG	Pyramid Histogram Oriented Gradient
PNN	Probabilistic Neural Network
PRO	Produit
RBF	Radial Basis Function
RGB	Red Green Blue
ROC	Receiver Operator Characteristic
ROI	Region Of Interest
SAE	Staked Auto Encoder
SCNN	Siamese Convolutional Neural Network

SIFT	Scale-Invariant Feature Transform
SNN	Siamese Neural Network
SR	Sparse Representation
SSO	Spatial Structure Optimizer
SURF	Speeded-up Robust
SVM	Support Vector Machines
TAR	Triangle-Area Representation
TOA	Triangle Oriented Angles
TPR	True Positive Rate
TSL	Triangle Side Lengths Representation
TSLA	Triangle Side Lengths and Angle representation
VGG	Visual Geometry Group

Chapter 1

1 General introduction

Contents

1.1 Context and problematic

The visual human system creates a mental image of the world we live in. It enhances our lives by describing the world's characteristics in terms of texture, color, context, and depth. For humans, describing or naming the visual scene is always a simple process; it may take just a few mscs to label an image of an object or scene. However, developing an artificial system that can achieve the same performance and robustness as humans is a challenging task. To perform artificial systems, researchers from various fields such as physiology, philosophy, psychology, engineering, computer science, and artificial intelligence are required.

Computer vision (CV) is a multidisciplinary field that attempts to mimic the process of the human visual system. It is considered as a field that comprises techniques for acquiring, processing, and comprehending pictures to make decisions. The principal goal of a CV is to understand the content of images and videos. During the last few years, computer applications have seen a significant shift from simple data processing to machine learning, thanks to the availability and accessibility of a huge volume of data collected through sensors and the internet. The idea of machine learning demonstrates and propagates the fact that computers have the ability to improve themselves with time. Several algorithms have been proposed in the literature during the last few years. Deep learning is becoming a common algorithm in the field of computer vision. Deep neural networks are highly efficient as a machine-learning technique for understanding high-dimensional data because they can learn important features for discriminating between classes from images directly and automatically.

An increased need for automation and a growing demand for vision-guided robotics and other industry-specific systems are driving the massive adoption of computer vision applications. Today, major technology companies like **Amazon**, **Google**, **Microsoft**, and **Facebook** are investing billions of dollars in computer vision research and product development.

Computer vision technology has several applications and may be used in a variety of sectors. Some use cases are hidden in the backend, whereas others are more obvious. Agriculture is one of the industries that has benefited from services provided by computer vision technology; according to the literature, numerous applications have been implemented for this sector that can currently recognize known plant and tree species by only taking a photo of the plant or just a part of it. We mention, for example **Lefsnap (**developed by the University of Maryland, Smithsonian Institution, and Columbia University and it is free for IOS**.)**, **iNaturalist** (is a joint initiative of the California Academy of Sciences and the National Geographic Society. Free on Android and iOS.), **Pl@ntNet (**Pl@ntNet is a plant biodiversity research and teaching program financed by the Agropolis Foundation since 2009.**)**, **Plantix (**is one of the most recent free plant identification applications for Android, It can diagnose disease, pest damage, and nutrient deficiencies affecting crops, and provide treatment recommendations. It is developed by a hybrid between a social media platform and a forum for gardeners and farmers**)**, and so on.

In general, the development of agriculture as a sector depends on plants. In particular, in this thesis and in light of the importance of the agriculture sector for human life, we have considered both tasks that concern plants, i.e., plant identification and plant disease recognition.

Accurate plant identification will help in understanding what should be used or avoided (toxic), how plants develop in terms of (shape, texture), and how to care for and protect them from pests. Accurate plant disease recognition is an important factor in determining the yield and quality of plants. An increasing global population calls for increasing food production. Early plant disease detection will help greatly in preventing plant product losses, which leads to preventing famine and gaining time and money.

Hereafter, we first give an overview and summarize some challenges associated with the task of plant leaf recognition, and then we give an overview of the second task with its own challenges.

1.1.1 Plant leaves recognition

Plants have a significant role in human life, whether in environmental aspects such as adjusting the climate, providing habitats for animals, and creating a natural way to prevent us from natural disasters such as floods and desertification, or in economic aspects such as medicine, cosmetics, and so on. There are over 3 million plant species in nature, each having distinctive features [1]. Identifying plant types or species is a critical undertaking for botanists and scientists in related disciplines as well. Knowing the species names means knowing how to deal with the plant. Due mainly to human civilization, such as hurbanism and manufactory, botanists have the arduous task of investigating as many plant species as possible before they go extinct. The major focus of this type of investigation is on documenting species distribution by establishing a database and more crucially, by preserving and identifying what is usefuel for humans and what is harmful. Identifying plant species based on classical field guides or identification keys is difficult to manage, and it takes considerably more time even for botanists and professionals. Plant species may be identified using a variety of organs, including leaves, flowers, fruits, and bark. However, the leaf organ attracted botanists' interest for a variety of reasons, including the fact that, unlike other organs, it remains visible throughout the year, is simple to photograph, and contains a number of distinguishing characteristics.

1.1.2 Plant recognition challenges

When it comes to recognizing leaf species, there are several problems or tasks to face. Natural resources (e.g., tree age, degree of leaf exposure to natural light); in addition, many other factors are provided that complicate the process of automatic plant species identification.

- **Large Intra-species variability (according to shapes)**

Variability is indicated for the same species. In this scenario, the leaves might be displayed with a varied contour and overall shape from the same species. Figure 1.1 depicts three leaves from the same species, each with a distinct shape. Even for professionals, the diversity within the same species makes categorization challenging.

Figure 1.1: Three samples from the same species with different shapes.

➢ **Large Intra species variability (according to the degree of exposure to a light source)**

The colors of leaves can vary depending on their exposure to the sun. Some leaves may be directly exposed to the light, while others are less (due to dense foliage around them for example). As a result, the color of certain leaves may change. Figure 1.2 depicts leaves from the same plant species but of a different color.

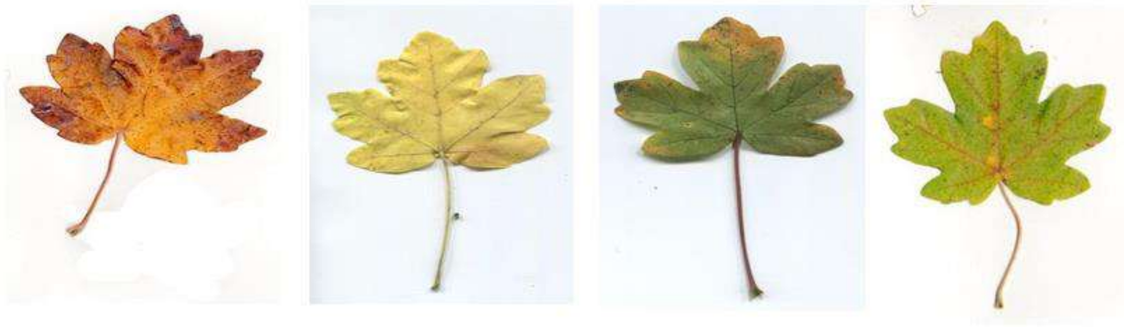

Figure 1.2: Same species with different colors.

➢ **Large Intra species variability (according to age)**

It is described as the diversity of the same leaf species within plants of different ages. Figure 1.3 depicts three samples of the same species belonging to a plant at various ages.

Figure 1.3: Variability according to the age.

- **Inter-species similarity**

In this case, botanists are confronted with leaves from diverse species that have similar characteristics (shape and texture). Three identical leaves from different species are shown in the Figure 1.4.

Figure 1.4: Different leaf species with similar shapes.

- **Large number of species**

The earth hosts very large number of species, and botanists have a difficult task in identifying all of them. Classifying a large number of classes (species) is more challenging than classifying a few number of classes.

Figure 1.5: large number of leaf species.

- **Difficulties of automatic vein extraction**

The low contrast between the venation and the remainder of the leaf blade structure makes the process of automatic vein extraction difficult.

Figure 1.6: low contrast.

1.1.3 Plant disease identification

According to the Food and Agriculture Organization of the United Nations (FAO), pests and diseases cause the loss of 20–40% of worldwide food output [2]. Statistics depicts that to fulfill the food requirements of a 9.1 billion population by 2050, a 70% increase in agricultural productivity is needed [3]. In the fact plant disease posing a serious danger to food security and famine. In addition to the problem of food security, economic losses in the other hand pose another serious problem. In many countries, agriculture is one of the most important industries for contributing to a country's income. Plant diseases alone cost the world economy roughly $220 billion per year [4]. Over the world several populations depend mainly on agriculture production such as in employment, export earnings, and food security. To overcome this, farmers, scientists, researchers, analysts, specialists, and government try to exert further effort and strategies to increase agricultural production to accommodate the needs. An early detection of diseases is highly needed to taking preventive measures, mitigate economic, and production losses.

Farmers tend to classify diseases based on the observation of several sections of the plant such that leaves, stem and products; however, leaves are the most often observed component for identifying an infection. Plant diseases caused by living organisms are classified as biotic [5]. Fungi, bacteria, and viruses are the primary causes of biotic diseases. And as abiotic diseases, which is caused generally by non-living ecological factors such as hail, spring frosts, meteorological conditions, chemical combustion, and so on. Abiotic diseases are non-infectious, non-transmissible, less harmful, and most of the time preventable. Plant disease categorization by humans is time consuming, costly, and requires an expert. To solve these issues, an automated plant disease system is extremely needed.

1.1.4 Plant disease challenges

In the process of detecting leaf diseases, there are several difficulties to address. The most significant one is the intra-variability of the same disease within the leaf. The disease can appear at any location on the leaf, with various shapes and colors, it might vary greatly depending on its stage of development and, in certain cases, where it is situated on the plant. Figure 1.7 illustrates four distinct leaves infected with the same disease, each with a unique shape and location.

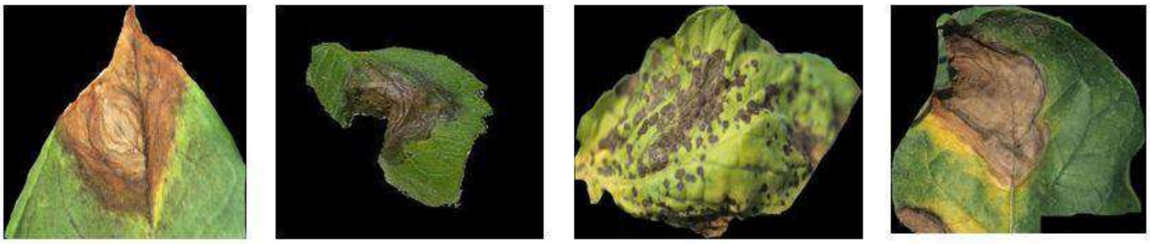

Figure 1.7: Alternzroise leaves disease.

Second challenges is presented by symptoms caused by distinct diseases may appear visually identical. Figure 1.8 depicts an example that illustrate similarity between two different diseases but share the same color.

Figure 1.8: Color similarity between two different diseases.

1.2 Objectives and contributions

Agriculture is the first human activity to contribute to humanity's progress and advancement. It is regarded as the backbone of numerous countries' economic sectors, such as medicine and cosmetics. Agriculture developements depends on the plants, so humans must pay close attention to preserve them. Plants are not only crucial to the human environment; they also serve as the foundation for the long-term health and sustainability of environmental systems. Aside from these significant facts, they have a variety of helpful applications, including medicinal and agricultural applications. In nature, there are millions of plant species, but due to human progress such as hurbanism and manufactories, some of them are at risk of extinction [6]. As a result, there is an urgent need to save plants from extinction. This is not the only issue confronting the agriculture industry; plants are also threatened by disease, which is regarded as the most serious problem that affects agricultural productivity. With a rising population, there is a rise in their demand for food to sustain their lives. In the fact the losses of agriculture production not only affects the food and raw materials, but it also affect individuals that consider it as a source of their income. Early and rapid diagnosis of plant diseases is very important to save humanity's lives from famine (food security) and unemployment.

In general, manually identifying plant species or diseases is difficult, time-consuming and necessitates the presence of expertise, which is not always accessible. Furthermore, a specialist in one species or disease may be unfamiliar with another. Our goal in this thesis is to present quick and accurate automatic plant identification and automatic plant disease detection in order to help farmers, botanists, and laymen in identify and preserve plants by presenting numerous automatic solutions utlizing computer vision, machine learning, and deep learning approaches.

The following contributions are proposed to address these two problems.

- **Contribution NB1**: **A study using Machine Learning of plant leaf identification.**

A comprehensive overview, including evaluation and understanding of relevant studies, is given. We primarily review existing leaf-based plant species identification methods, such as plant leaf features, feature extraction methods, classifiers, deep learning approaches and public databases. The objective of this contribution is to highlight the importance of plant species identification, give guidance and extensive research for those who are new to this topic in order to treasure and protect plant species (Chapter 2).

- **Contribution NB2: Plants species identification using computer vision techniques**.

According to the literature, the most distinguishing features that characterize plant leaf images are shape and texture. In our contribution, we proposed recognizing plant leaf species based on visual features, i.e., characteristics derived from a leaf image. Morphological characteristics are used to capture plant shape features, and texture features are used to represent the interior structure of leaf veins (Chapter 3).

- **Contribution NB3: Plant leaves classification using a modified multi scale triangular distance matrix.**

General features are intended for all types of objects (cars, leaves, characters, and so on). Their main advantages are of being simple and rapid. However, they don't provide a high-level of semantics. Leaf contour is sufficiently informative to distinguish botanical characteristics sections (base, apex, and around the center) and is easier to be extracted than the other feature venation. A discriminative shape feature that concentrates solely on discriminative parts has been proposed in contribution 3 (Chapter 4).

- **Contribution NB4: Automatic recognition of plant leaves using parallel combination of classifiers; contribution N5: Automatic recognition of plant leaves using serial combination of classifiers; and contribution N6: Comparaison study of multiple parallel combination schemes for automatic plant leaves recognition.**

Machine learning has attracted attention in recent years as a process of obtaining solutions to a wide range of problems by utilizing a variety of classifiers. Classification methods or classifiers are based on various theories and methodologies, and from the literarture no one has presented superior performance to another; it is always relative to the situation and considerations. In order to take advantage of each classification method, combination methods have been proposed as a solution. Our contribution aims to improve the identification of plant categorization results by considering different combination approaches into account. In contribution 4, we have explored two parallel combination techniques; in contribution 5, we have dealt with a sequential approach; and in contribution 6, we have investigated a comparison of numerous parallel combination methods.

- **Contribution NB7: Plant Leaves Recognition based on a Hierarchical One-Class Learning Scheme with Convolutional Auto-Encoder and Siamese Neural**

Network; and contribution NB8: Convolutional auto-encoder for plant diseases recognition.

Deep learning is an effective method developed in recent years, it can learn essential and important characteristics for differentiating between objects from raw images directly in an automatical way.

Deep learning has made significant progress in various areas such as computer vision, and many other fields. In contribution 7 rather than the conventional exploitation of deep learning architectures such as the Convolutional Auto Encoder (CAE) and Siamese neural network, in our case we proposed the Convolutional Auto Encoder (CAE) and Siamese as a new classifier by considering it as one class learning classifier. In our work, we propose a hierarchical plant classification system based on one-class learning. The hierarchy of our system consists mainly of two stages (clustering using K-means and classification using our novel proposed classifier). (Chapter 8).

Plant disease is a serious problem that threatens global food security. Early discovery of a disease can let farmers take appropriate precautions and reduce damage rates. We suggested an autonomous plant disease diagnosis system based on CAE as a feature extractor in contribution 8 (Chapter 9).

1.3 Thesis organization

Our thesis is organized as follows: **Chapter 2** is devoted to presenting the state of the art of plant classification that exists in the literature. The overview is organized into two subsections: the first subsection presents handcrafted features by addressing approaches that adopt common identification methodologies and techniques (general methods) and specific approaches that are based on botanical knowledge by exploiting different classifiers. In the second section, we present an overview of different deep learning architectures that have been proposed. Finally, the well-known datasets are presented. In **Chapter 3**, we present our contribution by proposing an automatic system based on shape and texture features. We give an overview of the proposed combination feature methods, and then at the end, we give the carried experiment. In **Chapter 4,** based on the analysis of the leaf outline, our contribution is based. We first define the general principle of the proposed method, then its details, and finally, at the last step, the experimental section is given. In **Chapters 5, 6,** and **7,** we present our contributions by first describing the general principles of classification methods or classifiers; then we describe a pipeline of two parallel combination schemes in **Chapter 5, a** serial combination method in **Chapter 6**, and finally in **Chapter 7,** we present extensive experimental parts of several parallel combination methods by using two well-known datasets. In **Chapter 8** we propose a novel classifier for plant classification based on a hierarchical strategy, since plants are organized in hierartches. We give an overview of the proposed model and the novel classifier, then at the end we give the carried experiment. In **Chapter 9** we give an automatic plant disease system using a deep learning algorithm.

At the end of the thesis, we highlight the main **conclusions** of the work and we propose some future work, such as establishing a dataset for Algeria plants.

Chapter 2

2 A Study on Machine Learning techniques in Plant leaf Identification

Contents

A Study on Machine Learning techniques in Plant leaf Identification

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Abstract

Plants serve an important function in the ecosystem; without them, the environment and human existence on our planet would be impossible to sustain. Their presence is unavoidable in this world for clean air, food, medicine, and water. Because there are so many distinct kinds of plants, human identification is difficult and time-consuming. In this study, we have examined the present state of research on computer vision approaches for the identification of plants. Given that feature extraction is a critical approach in computer vision, we investigated a variety of image processing techniques for the feature extraction of leaves. Furthermore, we give a description of the various classifiers used in the identification process. Currently, deep learning has been successfully applied to the plant identification system. We will present a study on deep learning, and finally the well-known datasets will be presented. Our findings reveal that deep learning outperforms existing commonly used image processing approaches in terms of accuracy.

Keywords: plant leaf identification, feature extraction, deep learning, Classifier.

2.1 Introduction

Advances in technology, as well as the prevalence of urban settlement, have undoubtedly contributed to a deficiency on the level of various environmental factors such as pollution, and global warming. Plants are one of the most deficient components, the earth hosts a huge number of plant species with around three million species, some of them are subject to the danger of extinction, and some others disappear every year [1]. Indeed, plant extinction has a very negative impact on human beings including climate change, flooding, and desertification [7]. With this in mind, there is a very urgent need to protect plants from extinction danger. Establishing a plant database, which catalogs the plant diversities, is the first step towards achieving such a noble target. Plants are immensely beneficial to human life because they form the basis of the food chain, and several medical treatments.

Plants can be identified by their leaves, flowers, roots, and fruits. Researchers [7] [8] consider leaves to be the commonly used and, unquestionably, the best organ for classifying plants due to their availability in all seasons of the year and slow growth. Furthermore, the flatness of the leaves allows them to be easily represented by a computer in 2D. In light of current advancements in mobile technologies and the importance of plants, a lot of projects share the goal of developing a smartphone applications (Leaf Snap, PlantNet, Picture this, and Folia).

From literature, several studies on automatic plant classification have been conducted [8]. This paper focuses on a review of related approaches for leaf image analysis. It details the methods presented in existing plant recognition systems. Various steps of the recognition process are examined in-depth by presenting the methods that are currently exploited, ranging from general to specific methods. Recently, deep learning has revolutionized the field of computer vision by automating feature extraction. In this work, we will provide an overview of various deep learning architectures that have been proposed to classify plants, and we will end it by presenting well-known datasets. The rest of this work is organized as follows. In section 2, a general scheme of automatic leaf recognition is presented. In section 3, a considerable number of feature extraction-based plant species recognition approaches, ranging from generic to specific, are discussed in detail. Different classification methods have been proposed in the literature. The common ones are presented in section 4. In section 5, deep learning based plant species recognition methods are introduced. In section 6, the public leaf image databases are presented. Finally, we discuss and conclude our work, and suggest future work in section 7.

2.2 General scheme of recognizing leaves

In general, the process of classifying leaf images consists of the following steps: preprocessing, feature extraction, and classification. Figure 2.1 presents the general scheme of leaf image classification.

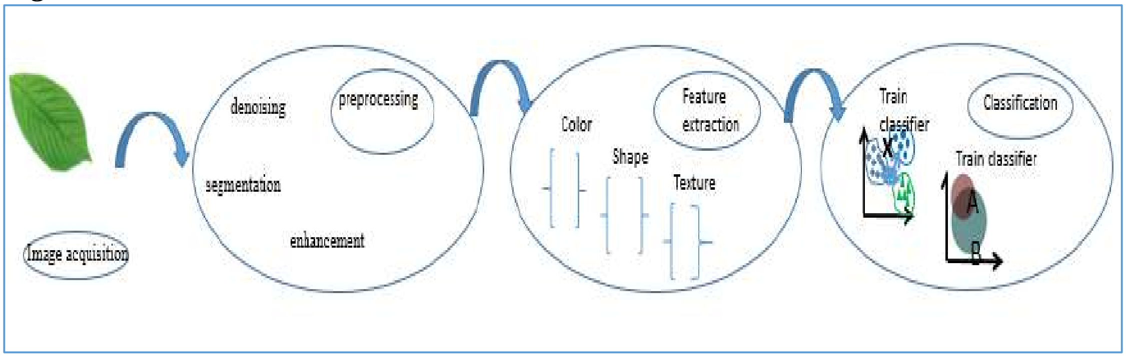

Figure 2.1: General Scheme of leaf image classification.

In any system in computer vision, after the acquisition of the image, there are three primary phases to consider: preprocessing, feature extraction, and classification.

The image obtained by camera or other devices, usually contains random noise and must be preprocessed.

Preprocessing consists of increasing the image's quality so that we can analyze it more effectively. We can reduce unwanted distortions and enhance some features that are required for the application we are working on by preprocessing. These features may vary depending on the application. Typically, it includes operations like image denoising, resizing, content enhancement, and segmentation. These can be applied in parallel or individually, and they may be performed several times until the quality of the image is satisfactory. The Gaussian and median filters, which provide a smooth blur to minimize image noise, are popular methods. The Histogram Equalization is another preprocessing technique used for contrast enhancement. It spreads out the most common pixel intensity values or extends the intensity range of the image to improve contrast. Histogram equalization permits the image’s sections with lower contrast to obtain a higher contrast. Image segmentation is another preprocessing technique, it used for locating objects and borders in images. It separates the Region of Interest (ROI) from the background. This improves the image of the leaf by removing background twigs, shadows, and so on. It highlights different features depending on the researcher's feature selection. For example, in the case of leaves, the segmentation could highlight margin, vein, and region pixels. The robustness of this phase will have a significant impact on the performance of the system identification. From [9] There are three types of segmentation methods: **manual segementation** is performed by the intervention of user, **automated segmentation** do not require user interaction it is performed using an algorithm, and **semiautomatic** it rely on segmentation based on either algorithm and user interaction.

Several methods have been used in the literature to segment leaves from images. However, the segmentation of leaves is dependent on the mode of acquisition. In the case of natural environmental, the leaf images are acquired with a cluttered background various evaluated methods have been proposed to segment this kind of image as in [10] [11]. In the simple case where the leaf of interest is clearly detached from its environment, the images will be presented with a uniform background, in this case processing graysclae image is sufficient for segmentation. A number of thresholding techniques have previously been proposed [12], a threshold is selected in an empirical (non parametric) or automatic (parametric) way. It based on the idea that the gray level of pixels in the foreground Image differs from that of the pixels in the background Image. If the pixel values are less than a certain threshold, these pixels are placed in one cluster, while other pixels are placed in another. Non-parametric approaches are more efficient and easier[13], but they may require an excessive amount of calculation time.

In [14] the authors used Otsu's thresholding method (parametric) to segment the leaf from the background. It is based on the image's gray level histogram, by evaluating the intra-class variance of the two components for each of the 256 possible values separated by threshold. The final threshold value is obtained based on the average of the two best thresholds identified during this process. Wiener filters were employed by the authors of [15] to remove noise from the image, Median filters to keep boundaries, and Histogram equalization for contrast enhancement. In [16] the authors propose to classifiy plants based on different leaf features and on ANN classifier, the Otsu thresholding method was used for the segmentation of leaf.

In [17] proposes a fully automatic segmentation method to classify natural leaf images. Experimental results show that the method is powerful but it is not speed in comparison to the Otsu method. In [18] The authors propose precise strategy to segment leaves they demonstrate that by first segmenting the pixels around the leaf border and using them to set the color distributions of an EM optimization, they can enhance the EM-based and classification-based techniques. They demonstrate that if the leaves are not on a complicated background, this basic approach yields a robust and accurate strategy. The EM [19] is it is probabilistic formulation of kmeans It is an iterative way to approximate the maximum function. The basic idea is to initialize a parameters estimate then Expectation step and Maximization step is repeated until the convergence of parameters. Another method is Guided Active Contour (GAC) [20] is a technique for segmenting tree leaves on a natural background. In terms of initialization tools, the use of current technology such as smartphones or touch screens allows the user to interact with the image and contribute additional high-level information through input strokes. Another enhancement is the use of a color distance map, which is used to enhance the contours and identify the various components of the image by comparing the similarity of the pixels in the image to the colors of the leaf. The similarity might be based on Gaussian distribution, linear regression, geodesic distance, or local mean. In [21] Four deep learning algorithms were compared for segmenting the leaves of digital plant images. They demonstrated that with these approaches, leaf segmentation could obtain an average accuracy of greater than 90%. They did, however, mention that the complexities in the background might affect accuracy. In [22] attempted to identify leaves based on their veins, they propose approach that combines a thresholding method with an artificial neural network classifier to extract vein patterns from leaf images. However, the two approaches discussed above are limited to single leaf image segmentation and classification with a simple or clean background [23].

2.3 Feature extraction

Feature extraction is a technique used for reduce a large input data to relavant features, the objective is to capture as many important features as possible to produce the best possible representation of the leaf images. The transformation of the input data into a set of discriminative characteristics is crucial step in classifying the leaf image. A good feature extraction and selection process should have numerous crucial charachtreistics such as identification, scaling, statistical independence and reliability, as well as invariance with regard to affinity, occultation, and immunity to noise. According to [24] [25] leaf features are classified into two categories: general visual features and domain-related visual features (specific to leaves). General visual features, such as color, texture and shape features, were not intended specifically for leaf images, but rather for all types of images regardless the content. Whereas, domain-related visual features are specified for leaf images, those features are based on the morphology of the leaf, such as shape, dent and vein. Figure 2.2 depicts a detailed overview of feature categories descriptors used to identify plant species.

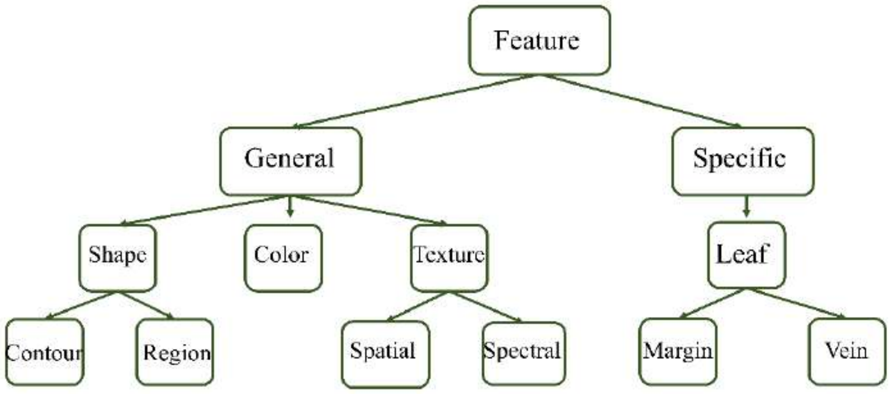

Figure 2.2: Overview of feature categories descriptors in plant species identification.

2.3.1 General approach

The general approach takes into account all features that are intended for any type of object. The visual aspect (color, shape, or texture) and location (whether it is from the complete (global) or from small regions of the object (local)) are used to describe objects in this approach.

1. Shape

A leaf shape is the most discriminative feature for differentiating between plant species because it carries several properties, and the overall leaf shape is preserved even with some damage, regardless of the age and season. Several existing methods in the literature focus on the shape of the leaf. From the literature, the mentioned methods for shape representation and identification can be divided into two types: contour-based methods and region-based methods [26]. In the first one, the shape features are extracted solely from the contour, whereas in the second, the shape features are extracted from the entire leaf region. Figure 2.3 illustrates the leaf contour and region.

Figure 2.3: illustration of leaf contour and region.

A. Contour

The contour-based descriptors consider only pixels from the shape edges. In the literature, a number of existing methods extract features from the contour, such as morphological features, MDM, IDSC, and so on. The extraction of the features is carried out either from the extreme controur or from the inside contour. In the following section, we will provide contour-based approaches that have been used in leaf identification systems.

- **Morphological features:**

Morphological features are obtained by extracting the leaf's basic geometrical properties [27], which include diameter, area, perimeter, major and minor axis length. Figure 2.4 depicts geometrical features extracted from a leaf image.

- Diameter D: is the longest distance between two points of the leaf contour.
- Area A: is the number of pixels that constitute the area of the leaf.
- Major axis length L_p: is the distance between two terminal points base and tip that is orthogonal to the minor axis length.
- Minor axis length W_p: is the longest distance orthogonal to major axis length.
- Perimeter P: the number of pixels at the margin of the leaf.

- Furthermore, and based on the aforementioned features, a set of digital morphological features are calculated, which are as follows:
- Aspect Ratio: is defined as the ratio of major axis length (L_P) to minor axis length (W_P). It is also called Eccentricity or Slimness. It is given by $Aspect\ Ratio\ = L_p/W_p$.
- Perimeter Ratio of Physiological length & width: this feature is the ratio of perimeter leaf and the sum of major and minor axis length, given by $PRPW = P/\ (L_p + W_p)$.
- Perimeter Ratio of Diameter: it is the ratio of perimeter to the diameter, given by $PRD = P/D$.
- Rectangularity: it measure the similarity between the leaf and a rectangle, given by $R = (L_P * W_P)/A$.

- Narrow Factor: the ratio of the diameter D and length Lp ($i.e., NF = D/ L_p$).
- Circularity: it measure the similarity between the leaf and a circle, given by the ratio involving the area A of the leaf and the square of its perimeter P, given by $C = 4\pi A/p^2$.
- Solidity: given as the ratio between A the area of the leaf and Ach the area of a convex hull, given by $S = A/Ach$.
- Compactness: ratio of the perimeter over the object's area; it provides information about the general complexity and the form factor $C = P^2/ A$
- Perimeter convexity P_c: ratio of the convex perimeter to the perimeter of the object $P_c = P/Pch$
- Sphericity: Ratio of the radius of the inside circle of the bounding box (r_i) and the radius of the outside circle of the bounding box (r_C) $Sph = r_i/r_c$. Figure 2.4 illustrates morphological features.

Figure 2.4: Morphological features.

- **Descriptors based on relationships between contour points:**

The principle of descriptors within this category is that points are sampled from the contour before performing spatial relationships between contour points. In what follows we will provide a number of existing methods that fall under this category.

Belongie et al, [28] proposed Shape Context descriptors. The basic idea behind shape context is to sample N point on the contour, from each point p_i we calculate the distribution relative to the other $n - 1$ points (where $i \neq j$ ($p_j$other points)). The distribution of the points is represented by a $2D$ histogram in the log polar system. h_i = (log (R_j), θ_j), where R_j denotes the euclidean distance between two points (p_i ,p_j), and θ_j represents the angle between the vector p_{ij} and the horizontal vecteur. After finding the correspondence between two shapes (find for each sample point on one shape the sample point on the other shape that has the most similar shape context), then the matching between two shapes is calculated. An improved version of shape context (known as IDSC, Inner Distance Shape Context) has been proposed in [29]. It is based on essentially the same principle as the Shape context, but instead of using Euclidean distance and the simple polar transformation as bin coordinate spaces, it uses the inner distance, where the length of the shortest path between landmark points within the shape boundary is defined as inner-distance and inner angle. A huge number of histograms are calculated and compared making the overall technique expensive thus have conducted to other improvements to the shape context descriptor in the identification of leaf species have been presented [30]. In the context of descriptors modification, they mainly evaluate two aspects: the entire calculation sets (the points on which it is calculated) and the entire vote sets (the points in relation to which it is described) preserving or increasing the shape matching precision. They based on the hypothesis that providing two different sets of points that have different roles in the shape context scheme and selecting them appropriately will help to achieve good results. There are therefore three alternative configurations: SC0, SC1, and SC2, where in SC0 and SC1 the sets calculation and voting are the same and constituted respectively of the points outline and points of interest (obtained by the Harris detector). Where SC0 represents the shape context descriptor and SC1 aims to define if the spatial relationships between salient points on the leaf area can describe leaves and if the number of salient point affects the results. On the other hand, in the third configuration SC2, the calculation set contains the points of interest and the voting set contains the outline points. Results have demonstrated the efficacy of the SC2 descriptor. The IDSC descriptor for plant leaf classification achieved a good performance, but it cannot capture local information of leaf margin.

Wang et al in [31] define the CCD (Centroid-ContourDescriptor) descriptor. The basic idea of the method is to extract a center of gravity from the leaves and sample points along the contour. The distance between each point and the center is utilized to compute the descriptor. In [14] , the authors present the ACD (Angle Contour Distance) descriptor. Its principle is to sample points from the contour and define a circle around the leaf that has the same perimeter contour as the leaf with points. The primary concept is to define the difference between two angles' absolute values. The first angle is calculated using the center of gravity and two contour points, one of which is the departure point and the other one is from the contour, while the second angle is defined in the same way as the first, with the exception that the two points are samples from the circle, not from the boundary of the leaf. In [31] the authors propose an amelioration version that involves the minimization of the considered points by selecting only the skeleton neighbor point of the leaf contour. The global features have the property of being insensitive to noise, but the matching performance on deformation and occlusion is not good due to the missing of local details.

- **Descriptors based on Multi-scale representations:**

The multi-scale descriptors provide a lot of information about the leaf contour. It extracts image features at multiple levels by capturing local and global features from low-to high-resolution scales. They are characterized by the highest discriminating power and noise resistance because they are based on the boundaries of leaves rather than image regions. From the literature, various methods have been proposed under this category, for instance. MDM is a global feature proposed in [32] that reflects a point distance at several scales. The feature is built using a distance matrix of $n * n$ points. The main idea is to sample n point with uniform distance from the contour, then calculate the distance between each point p_i where $i = (1, ..., n)$ and the other points, this distance matrix is symmetric with all diagonal value being zeros. Following the calculation of the distance matrix, each column of matrix D is moved up circularly such that the first element becomes zeros, then the matrix is sorted ascendable. This produces a new matrix D_m, with the first row having solely straight zeros with redunency. The MDM matrix is formed by reducing redundancy, the first row represent the distance of point with itself. MDM have advantages of the invariance to translation, rotation, and scaling. It capture fine and coarse geometry. In [33] The Multi Scale Triangle representation was proposed. In this method the shape is characterized by local features; triangles are used to capture the concavity and convexity of points. The method is based on sampling a collection of sample points from the boundary that are uniformly spaced and numbered in a clockwise. Each point p_i is represented by N_s (number of triangles of various scales where the points for drawing the triangle. For each point p_i, four triangle representations T_i^s (s represent the scale) are defined after the construction of triangles at varying scales: the first one is triangle area representation (TAR) it represent the signed area of triangle. The second one is Triangle oriented angles (TOA) represented by two oriented angles, this representation provides information about local concavities and convexities, the third one is (TSL) triangle side length, it represent the length side of the triangle , the last one is (TSLA) it present the same representation of TSL with the addition of a vertex angle at point p_i. Wang et al [34]introduced the multi-scale arch height (MARCH). It describes a hierarchical representation of the contour, which is defined by contour segments at various scales. Each p_i point is presented by height on a different scale. A contour point p_i height is defined by its perpendicular distance from its chord in the MARCH method, which may be considered as the height of an entire triangle for parameter K with all of its vertexes on the shape contour. To do this, each contour point undergoes a hierarchical arch height extraction at the K-scale. MARCH outperformed the state-of-the-art on four leaf datasets in terms of classification rate and retrieval accuracy, and it is integrated into a mobile application. In [35] the authors used a curvature scale space (CSS) image to illustrate leaf morphologies for Chrysanthemum variety characterization. The basic idea is to create images using a multi-scale organization of contour inflection points smoothed by many Gaussian filters in croissant order. The inflection points (also known as zerocrossing) are the locations at which the sign of the curvature changes. The maximum location positions (or peaks) of the CSS image are represented as CSS descriptor components, and they are utilized to represent leaf shape.

- **Descriptors based on transformed spectral:**

A leaf shape in this category can be studied in the frequency domain instead of the spatial domain**.** From the literature, Transform Fourier is the most used leaf descriptor within this category. Fourier descriptors (FD) are a classic shape identification tool that has developed into a generic way for encoding multiple shape characteristics by using a Fourier transform. For the leaf contour, a certain number of Fourier harmonics with only four coefficients are determined. In low frequency terms (low number of harmonics), these Fourier descriptors capture global shape aspects, whereas in higher frequency terms they capture finer shape details (higher numbers of harmonics). This strategy has the advantage of being simple to adopt. FD was combined with Morphological features in [36]. The researchers found that employing FD rather than Morphological features alone yielded better classification results. However, integrating all descriptions yielded the best outcome. In [37] employed FD in combination with Tchebichef Moment Invariant and the length of the major axis.

- **Descriptors based on point of interest**

Point-of-interest descriptors are created by selecting first scale-invariant key-points (interest points) in an image and then extracting for each key-point a local descriptors. The key-points from one image can then be compared to those from another. A high degree of key-point matching between two images implies that they are identical. Various methods that have been proposed in the literature are categorized as Point-of-interest descriptors, as instances **SIFT** [38] **(Scale-Invariant Feature Transform)**. It is a local characteristic based on the extraction of the key point (defined as the extremes of the DoG difference of gaussian) from the item, then for each location a centered window is used to compute a local oriented histogram. The histogram is oriented in the direction of the concerned point or location, in order to guarantee rotational invariance. The histograms are then normalized and concatenated to create a 128-dimensional representation. A reliable results has been achieved in [39] using SIFT and grid based colour moment to classify plant. SURF is another Point-of-interest descriptor. In [40] authors proposed Surf Speeded-up Robust it is built on the same concept as SIFT, However SURF descriptor have accelerate the process by reducing the cost complexity. SURF obtains the keypoints based on the Hessian matrix. This process has simplified the operation and helps to reduce the computational cost by applying an appropriate filter to the integral image. Haar wavelet responses in x and y directions are computed to determine the orientation. Several strategies for describing the local context have been proposed in the literature [41] [8]. All of the methods are based on the same principle: obtaining a descriptor by exploiting a window around the key point where the size and orientation are determined, then a matching operation on the correspondence between the points of images is performed.

B. Region

Region-based procedures, as opposed to contour-based methods, take into account all of the pixels inside a shape region to generate the shape representation. In this section, we only present the most frequently used region-based descriptors for plant species identification.

- **Hu moment:**

The Hu moment [42] is a descriptor that has been used to describe the shape of a leaf based on its region. It considers a set of pixels that will be characterized and analyzed as well as their distribution in the image and the relationship of one pixel to another. The method is based on moments, is a mathematical concept that comes from statistics and probabilities. It uses moments in the context of numeric images. The order 0 represents the area of the object m_{00} .The general formulation of the ordinary moments of an image I is represented as:

$$m_{pq}(I) = \sum_{x}\sum_{y} x^p y^q I(x,y) \qquad p,q = 0,1,2 \qquad (1)$$

The moment order1 used to determine the coordinates of the center gravity of the image $(\bar{x}, \bar{y})$. The central moments is represented by

$$\mu_{pq} = \sum_{x;y}(x-\bar{x})^p(y-\bar{y})^q \quad \bar{x} = \frac{m_{10}}{m_{00}} \ , \quad \bar{y} = \frac{m_{01}}{m_{00}} \qquad (2)$$

The moment order 2 gives a representation of the distribution of the pixels of an object around its center of gravity.

Thus, the central moments are invariant to translation and may be normalized to turn also invariant to scaling through the relation:

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\frac{p+q}{2}+1}} \qquad (3)$$

The moments of order 3 measure the dissymmetry

The values of seven Hu geometric moments can then be calculated from the normalized central moments as follows:

$$\varphi_1 = \eta_{20} + \eta_{02}$$

$$\varphi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}{}^2$$

$$\varphi_3 = (\eta_{30} - 3\eta_{12})^2 + (\eta_{03} - 3\eta_{21})^2$$

$$\varphi_4 = (\eta_{30} + 3\eta_{12})^2 + (\eta_{03} + 3\eta_{21})^2 \qquad (4)$$

$$\varphi_5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})((\eta_{30} + \eta_{12})^2 - 3(\eta_{03} + 3\eta_{21})^2)$$

$$+ (\eta_{03} - 3\eta_{21})(\eta_{03} + \eta_{21})((\eta_{03} + \eta_{12})^2 - 3(\eta_{30} + \eta_{12})^2)$$

$$\varphi_6 = (\eta_{20} - \eta_{02})((\eta_{30} + \eta_{12})^2 - (\eta_{03} + \eta_{21})^2) + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{03} + \eta_{21})$$

$$\varphi_7 = (\eta_{30} - 3\eta_{12})(\eta_{03} + \eta_{21})\ ((\eta_{03} + \eta_{21})^2 - 3(\eta_{30} + \eta_{12})^2)$$

These normalized central moments is used to calculate rotation invariant values by non-linear combination.

From the literature, several methods have used Hu moments for plant classification. For instance, in [43] the authors proposed a method that is based on the combination of contour descriptor (MDM), margin descriptors such as (Average Margin Distance (AMD), Margin Statistics (MS)), Morphological Features and Hu moments. A higher classification accuracy is reached by using MDM and Morphological features with Hu moments alone. In [44] the Hu Moments were exploited to identify plants. The advantage of these descriptors is that they release a reduced values number of the geometric characteristics of the shape (dissymmetry, elongation) only via statistical considerations, and they ensure an invariance of these measurements at the same time with the translation, change of scale, and rotation. However, in the context of image analysis, higher order moments have not been addressed, and comprehensive image recovery from such moments appears to be challenging [45].

- **Zernike:**

Zernike descriptor is proposed by [46] based on the Zernike polynomial and it forms a set of orthogonal polynomials on the unit circle. After centering the image on the unit circle, the sum of the values of the first 16 polynomials in the region allows us to define 16 moments with the same invariance qualities as the Hu moments. Its higher-order polynomial generates global shape information, whilst its lower-order polynomial generates local shape information. They introduced the Zernike moments, which consist of a set of independent and invariant moments of arbitrarily high order, to recover an image from moments based on the theory of orthogonal polynomials. The orthogonality characteristic of Zernike polynomials contributes to achieving a near-zero value of redundancy measure using a set of moment functions [45]. In [47] researchers have proposed to combine Zernike moments and Hu moments to identify plants with complicated backgrounds. In [1] authors demonstrate that categorization of plant leaves using morphological features and Zernike moments produced good results. The experiment was run on two different datasets.

2. Texture

The texture feature corresponds to the leaf's micro-veins. The texture feature is one of the most discriminative features, however in the literature it is rarely exploited alone for plant classification due to the challenges in its extraction. Micro-veins are tiny veins that run throughout the blade leaf, it necessitates high-quality image capture techniques. A traditional framework of leaf acquisition with standard cameras or scanners is insufficient. Figure 2.5 depicts micro-veins for leaf analysis. From the literature several researchers have others integrated texture with other descriptors, such as shape, color, and vein. In general, texture features can be classified into two main categories: spatial and spectral.

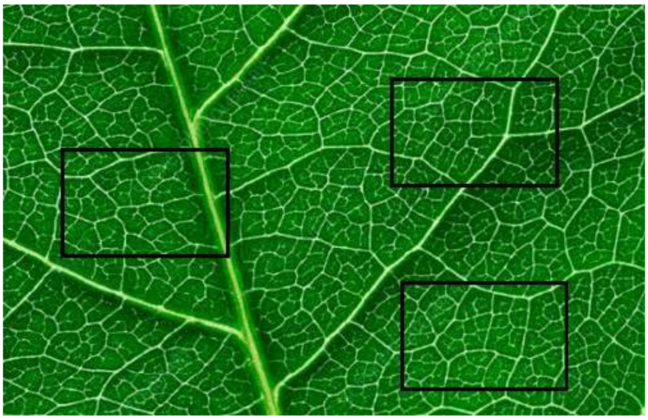

Figure 2.5: Leaf micro veins.

In this section, we will go over texture techniques that have been used in leaf identification. A Local Binary Pattern (LBP) was proposed as a statistical method by [48]. A feature vector is calculated using a very small local neighborhood (patch) of a pixel. The calculation of LBP descriptors is performed by first dividing the image into blocks, then the center pixel of each block is used as a threshold. Based on the comparison of the threshold with its neighbor pixels, binary values are generated. The technique is repeated until the histograms of each block are obtained and concatenated to produce a feature vector describing the image. In [49] the authors presented a modified local binary pattern, the method considers the structural relationship between neighboring pixels and replaces the approach of basic LBP by the mean (μ) and standard deviation (σ) of the whole neighborhood. In [50] To extract the LBP histograms for each scale, each image is partitioned into many equal overlapping blocks. A multi-scale pyramid is used first to increase the exploitation of leaf data. GLCM is another texture feature that was proposed in [51] it is one of the most widely used texture descriptors for capturing the leaf morphology. It is computed based on two parameters: the distance and orientation. To calculate the GLCM descriptor, images are first converted to grayscale, then a gray level co-occurrence matrix is built by calculating the occurrence pairs of pixels with defined values and in a specified spatial relationship that occur in an image. Finally, from the obtained grey covariance matrix, statistical measures are calculated (contrast, homogeneity, energy, correlation, and so on). In [52] A combination of LBP and GLCM was applied to classify tea leaf. In [53] the authors propose to classify plants using the co-occurrences matirix of different scale Gabor filters. Good results have been achieved.

3. Color

For several applications color is discriminant characteristic, but this is not the case for leaves, because leaf color changes with the seasons and geographical location. Color characteristics can be derived from images or regions after providing a color space (HSV, RGB, (HSI), hue-max-min-diff (HMMD), and LUV (L stands for luminance, whereas U and V represent chromaticity values of color images). In the literature, a number of general color descriptors, such as color moments (CM) [54] , color histograms (CH) [54], color coherence vectors (CCV) [55], and color Corre-lograms [56], have been proposed for image identification. Color in the context of leaves is an insufficient descriptor due to several reasons such as variation in intensity, hue of sunlight falling from different angles, fluctuations in illumination, and shadowing. As a result of these issues, numerous researchers have coupled color with other features to classify plants [57] [58].

Figure 2.6: Color Variations.

Zhao et al. [59] designed an Android-based mobile application to automatically classify plant species. Researchers combined the PHOG, Color, HSV, wavelet, and texture features after the segmentation stage, the features were extracted. All the experiments were carried out on the Leaf database of 126 species. The PHOG is a spatial pyramid representation of HOG. After providing edge detection, the image is divided by spatial pyramid into grids, then the magnitude and angle (the histogram of oriented gradient) for each grid is computed. The final PHOG descriptor is represented by the concatenation of all vectors at each pyramid. HSV color features can be represented by three types of attributes, namely: Hue (H) refers to the wavelength of the light reflected from an object or coming through, Saturation (S) refers to the color depth, and Value (V) refers to the color brightness. For the color moment three central moments of an image's color distribution (Mean, Standard deviation, and Skewness) have been extracted; and in order to capture the frequency the Wavelet has been used. In [60], authors built a foliage plant identification system. Zernike moments were combined with other features (namely geometric features, color moments, and grey-level co-occurrence matrix (GLCM)). The authors of [61] have identified medicinal plants such as herbs, shrubs, and trees. NN and Support Vector Machines (SVM) have been investigated for the classification stage with color and texture (Edge Histogram (EH) and Edge Direction Histogram (EDH)) for the feature extraction stage. Classification based solely on color histogram feature gives lower accuracy, because majority of the plants have green color. Hence, a reliable results has been achieved by the combination of the two features color and texture (edge) features. The results indicates the classification based on the SVM classifier is better than the neural network classifier.

2.3.2 Specific approaches

Specific approaches are descriptors that are distinctive to the topic of research. Knowing the searched object or item gives the ability to create or to design a specific descriptor for this object. There are a number of descriptors that have been created specifically for leaves that consider the anatomical properties of leaves such as tooth, margin, vein, apex, and so on. Botanists used leaf anatomical characteristics to aid in the discrimination between plant species.

1. Shape

The shape of the leaf limb is regarded to be the most distinctive characteristic [62] [63]. Distinct species have different leaf tips, apexes, and edges (tooth, blades, and other characteristics). Figure 2.13 illustrates the discriminating parts of the leaf. All leaves may be generally classified into two main categories: simple with a single leaf blade or compound with many leaflets. Pinnately, palmately, and doubly-leaves represent compound leaves. From the literature [7], the majority of research classify plant species using simple leaves, because compound leaves are made up of basic leaf-like components. In the compound leaves, the basic leaf is called a leaflet. Figure 2.7 illustrates the leaf category.

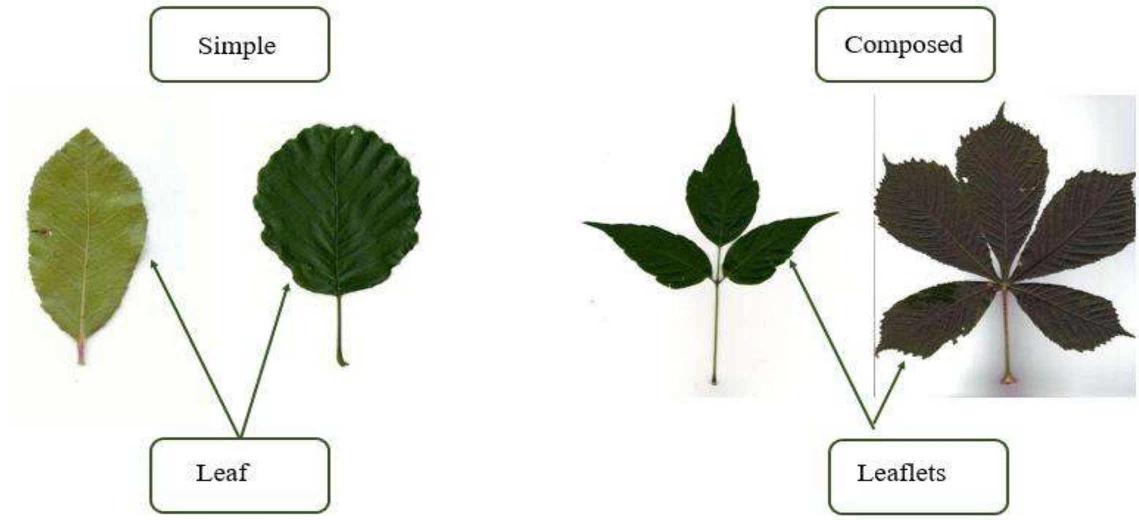

Figure 2.7: Leaf category.

Local specific features refer to the representation of particular leaf parts (margin, apex, and base). Discriminant sections of a leaf are depicts in Figure 2.8. Leaf apex is represented by the upper region and the base is the lower part of the leaf.

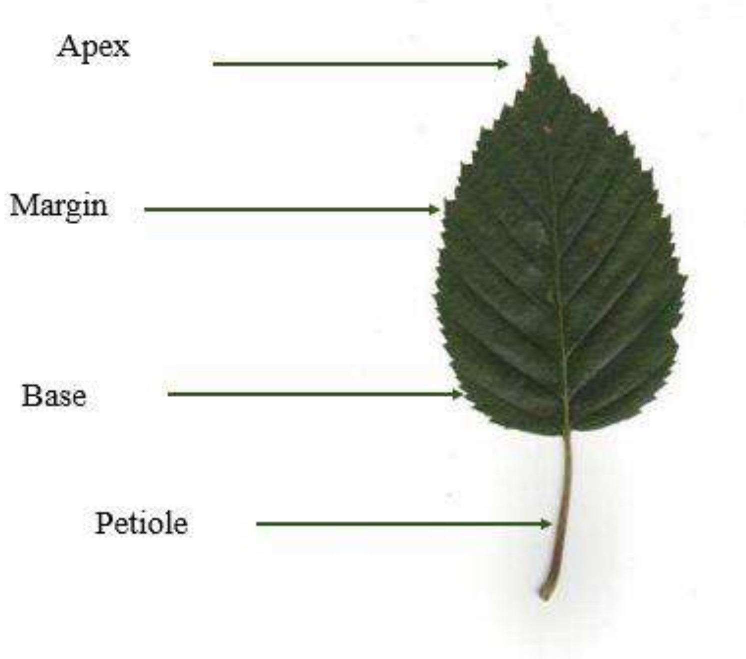

Figure 2.8: Leaf discriminant parts.

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Leaves have different apex shape. Figure 2.9 depicts different leaf apex shape part from distinct species**.**

Figure 2.9: leaf apex.

Leaves have different base shape. Figure 2.10 depicts different leaf base shape part from distinct species**.**

Figure 2.10: leaf base.

In the literature, several methods for identifying botanic characteristics have been presented. One of the most challenging issues that confronted researcher in the process of automatic identification, released on the extraction of characteristics from leaf images. To address these mentioned issues, some studies [64] [65] extract the features manually or semi-automatically by using a restricted database of species or drawn images. In what follows, we will present an overview of the specific approaches that have been proposed in the literature.

In [66] use botanical geometric analysis to define the terms simple and compound leaf. The core idea behind their method is to compute features from certain locations along a contour, such as maxima (concave, convex), and inflexion points. The features are primarily concerned with the frequency and geographical distribution of maxima concave, maxima convex, and inflexion points. They eliminate all triplets (made of the maxima and the two-sided neighboring inflexion points) if they are aligned in order to pinpoint only the points that describe the lobes and leaf variation. Leaf images can be classified as simple or compound based on the number of inflexion points. The experiment was conducted using the public dataset, yielding a 97.93 percent accuracy. The percentage of misclassified photos (images allocated to the erroneous category) (0.92 percent) and the percentage of unclassified images (2.67 percent) make up the error rate (1.75 percent). In [67] The authors propose to classify leaf images by first categorizing them into three types: simple lobed, simple not lobed, and compound. Lobed leaves have well-defined projections from the leaf midribs to the individual veins, whereas compound leaves have blades that are split into several leaflets and linked to the same central vein. Second, the authors divided the complete leaf picture into three semantic sections: top, middle, and base, and in order to find the suitable species a combination of descriptors based on shape and texture for each portion of the leaf is performed. According to the authors, leaf variety complexity is decreasing within and between species, because of the definition of relevant characteristics for each (part) based on its discriminating properties.The authors of [68] create an automatic leaf recognition system. The curvature of the leaf base and apex is described by the Centroid Contour Gradient (CCG). Prior to the application of the procedures, the normalizing step of discriminant leaf parts was used (the normalization consists of making the upper part of the leaf symmetry). The Contour Gradient (CCG) works by calculating the gradient between pairs of pixels in the leaf boundary that correspond to the interval angle. The experiment was conducted using a dataset belonging to four different sorts of groupings (acuminate, cuspidate, obtuse, and acute). In terms of accuracy, good results has been achieved. [69] Cerutti et al. present an active polygonal model for predicting the shape of simple leaves and leaflets. In the first step, by estimating each leaf's length, width, bilateral width, base and apex angles (or leaflets), an energy function based on a color dissimilarity map is minimized for each stage. To crudely identify a potential leaflet region, an extra model is used that approximates leaflets to uniform circles stacked in pairs on either side of the main axis. The user must first define the leaf type (simple or compound) and initialize the model's length, breadth, bilateral width, base, and apex before applying the polygonal model. An accuracy of more than 80% is achieved by giving the correct the species among the first five answers.

The shape of the leaf edge is considered as one of the most distinguishing features used by botanists when identifying leaves; it contains a wealth of information about the leaf, including tooth spacing, quantity per centimeter, and qualitative descriptions of the flanks (for example, convex or concave). According to a review in [27], the leaf margin has seen little application in automated species identification, with just 8 out of 106 publications focused on it. This is owing to the difficulty in identifying it from an image, primarily due to its small scale on a higher level (image).

In [69] the authors proposed a strategy based on leaf margin as descriptors. The method CSS extracts teeth and pits along the leaf margin; the descriptor describes tooth and pits as sequences (size, curvature (positive or negative), vertical location according to the apex and base). The Nearest Neighbor classifier (NNC) is utilized in this study to categorize species using the distances of these sequences. This method logically conveys information about leaves.

In [70] the authors suggest a technique for automatically identifying species based on a sparse representation of the leaf teeth. Corners are frequently utilized to represent the image leaf teeth. The leaf margin is represented by four morphological measurements: (1) total number of teeth, (2) the ratio of teeth to the length of the leaf margin expressed in pixels, (3) leaf-sharpness, and (4) leaf-obliqueness. Leaf-sharpness is calculated by connecting the top and bottom edges of the leaf teeth to form an acute triangle. Many triangles corresponding to leaf teeth are obtained for a leaf image in this way. The acute angle of each leaf tooth is used as a plant identification criterion in their method; the last attribute (leaf-obliqueness) is calculated from the triangle of each tooth as the ratio of the height and base. For the eight species tested, the proposed technique obtains a categorization rate of roughly 76%.

2. Veins

The vein is another discriminant feature to characterize between species that takes into account the botanist. The structure of leaf veins can be parallel, palmate, or pinnate. Each species has its own structure. The apparent presence of veins is mainly due to their high contrast with the rest of the leaf blade. In [71] their findings reported that veins represent a high importance. From the literature only few studies examined venation as a feature alone. As instance in [72] the authors propose to classify vegetable leaves based on the veins morphology, the segmentation was performed based on the unconstrained hit-or-miss transform to extract veins, a reliable results has been achieved. In [73] the authors identify leaf based on vein morphometric features and on different deep learning architectures with several machine learning algorithms, for veins morphometric features the veins were obtained using sobel and skeleton techniques.

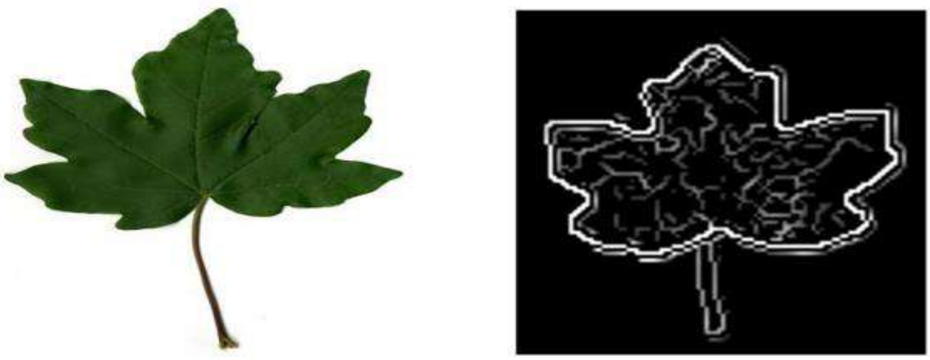

Figure 2.11:Leaf Veins.

2.4 Classification

The classification stage takes the feature vector defined in the previous stage and maps it to a confidence score using a classifier. The categorizing of new data into a collection of classes is known as classification. In general, it entails teaching a system to take a set of labeled attributes as input and is known as supervised classification or it entails teaching a system to take a set of attribute and is known as unsupervised classification. Several models have been established for data categorization; however, in our study we will focus on the most frequently used models in the plant classification domain.

SVM (Support Vector Machine) [74] is one of the most popular classifiers used in image classification and for plant classification also [75] [50]. Its basic idea consists of defining an optimal hyperplane that separates two classes. It was natively developed for binary classification problems. Several improvements to SVM have been proposed to extend it for multi-class problems and non-linearly separable data. Those notions make these method attractive for reserchers in the classification of complex data. In [76] Propose to classify plant species based on 19 leaf venation features and a Support Vector Machine (SVM) with an RBF kernel. In [77] The author proposes to identify plant leaf based on visual features using different artificial intelligence techniques such as artificial neural networks, a naive Bayes algorithm, a random forest algorithm, K-nearest neighbor (KNN), and a support vector machine (SVM). The best result were achieved by the SVM classifier. In [78] Propose morphological features and the support vector machine (SVM) with the adaptive boosting technique to classify plants.

KNN (K Nearest Neighbors) is a non-parametric classification algorithm[79]. This technique is used to classify unknown samples based on their nearest neighbors. To categorize an unknown sample, the nearest k training instances are employed. The most common class among these k neighbors determines the class of this sample. There is no time set aside for training in KNN. However, because all computations are performed at one time, testing takes a long time. Several plant identication systems use KNN as a classifier. As instance, in [80] authors introduced a two-stage plant species detection algorithm that combines local K-nearest neighbors and weighted sparse representation. In [81] K-nearest neighbors were employed by the authors to identify species that are closely related to the training samples. According to the authors using the Cosine KNN classifier and PCA technique with gist feature vector outperformed Pattern-net neural network and SVM techniques. Researchers in [82] have developed a recognition system that can identify leaf plants based on a set of features such as geometrical, distance map, color histogram, and centroid-based radial distance map. A k-Nearest Neighbor is proposed to classify leaf images. An accuracy of 83.5% was obtained.

Naive Bayes A bayesian classifier [83] is a statistical model. It is based on the Bayes' Theorem and the assumption of predictor independence. A Naive Bayes classifier is based on the assumption that the presence of one feature in a class is independent of the presence of any other features. Conditional independence might reduce accuracy, which is an inconvenient characteristic of this classifier in some cases. A number of reserchers have been considered NB as a classifier. As instance in [84], the authors propose to identify plant leaves using texture and shape for the feature extraction stage and the Naive Bayes approach for the classification stage. Results reveal that the model has good classification accuracy. In [85], to distinguish between plant leaves, shape and color features are extracted from leaf images, and then several classification techniques such as k-Nearest Neighbor, Support Vector Machines, Naive Bayes, and Random Forest are proposed to classify plants. In [86], present an evaluation of the performance of several classifiers on the plant leaf dataset, including the Decision Tree classifier, the Naive Bayes classifier, and the K-Nearest Neighbors algorithm.

Neural Networks [87] It is intended to simulate the behavior of the human brain in its original design. These networks' definitions may potentially have a probabilistic component.

Training such a system enables the adjustment of the weights and transfer functions that govern its behavior. To perform automatic plant recognition, in [16] Plants are classified by authors using a combination of morphological features, Fourier descriptors, and a newly suggested shape-defining feature. These characteristics constitute the artificial neural network's input vector (ANN). Using 14 classes, good results were obtained. The author in [88] employs a Multi-Layer Perceptron (MLP) artificial neural network with different feature extraction techniques. A comparison of the MLP algorithm against other supervised learning approaches on leaves is performed. The acquired findings demonstrate that the MLP algorithm outperforms the other techniques. The authors [89] evaluated the efficacy of the Extreme Learning Machine (ELM) on a plant leaf dataset compared to several other classifiers. Multiple image processing and feature extraction approaches have been exploited.

Linear Discriminant analysis (**LDA**) [90] is one of the most extensively used supervised algorithms with applications in a variety of high-dimensional classification tasks. The main idea of LDA is to discover a linear transformation that best distinguishes the classes and then classify them in changed space using metrics like Euclidean distance. The authors [91] present a classification strategy for categorizing different types of plants based on a combination of shape, first-order texture, Gray Level Co-occurrence Matrix (GLCM), HSV color moments, and vein characteristics. For the classification, LDA and RF are proposed. Results demonstrate that LDA outperforms RF with a classification accuracy of 92.65%. In [92] the authors present an automated leaf classification system based on a serial combination of two classifiers: linear discriminate analysis and Nave Bayes. In this work, the system is composed of two stages. In the first, the NB classifier attempts to discover the class to which a given sample belongs by using a reject option. If the sample's confidence score from NB does not surpass a specific threshold, it will be subjected to the second stage LDA classifier.

2.5 Plant identification using deep learning

Features extraction and deep learning are the main two approaches of artificial intelligence. For the first one, features are chosen by hand and extracted using pre-programmed algorithms. Then the most representative features that describe the image data are selected. However, this procedure is complicated and needs adjustments and recalculation for each problem or data set. Recently, to overcome the drawbacks of already used traditional algorithms, deep learning has been presented. From images, it can directly and automatically learn essential characteristics for differentiating between species. Deep learning is a subset of machine learning approaches, its idea is inspired from brain human biological neural networks, in the fact it consist of several processing layers that allow representation learning of multiple level data abstraction. Backprogation techniques is used to train the DL, several techniques has been introduced to improve results such as data augumentation which is a set of artificailly techuniques increase the data by generating new data. A reliable results has been achieved for many applications using Deep Learning techniques.

In recent years, different deep learning architectures have been widely exploited to classify plants (CNN, Siamese, and Auto-Encoder so on), promising results have been recorded compared to other machine learning techniques. An overview of some relevant works is presented below.

Convolutional Neural Network (CNN)

Convolutional neural networks, also known as ConvNets, were first introduced in the 1980s by Yann LeCun [93]. The early version of CNN was called LeNet (after LeCun). In 2012, with the availability of large image datasets ImageNet and computational resources this has allowed researchers to develop complex CNNs (AlexNet). Good results have been achieved to the document recogntion. The significant results of CNN were obtained by the effective utilization of GPUs, the ReLU [94] activation function, the dropout regularization approach, and data augmentation. Convolutional neural networks are are a specific type of artificial neural networks (ANNs) it is composed of multiple layers, each of its layers generates various activation maps. The CNN composed by a set of layers that may be classified according to their functions; into three basic types of layers are: convolutional layers, pooling layers, and fully-connected layers.

- Convolutional layer:

One of the essential building blocks of a convolutional neural network is the convolution operation. The parameters of the convolutional layer are consist of a collection of learnable filters (kernels). A nonlinear activation function such as (sigmoid, tanh, ReLU etc.) follows the convolution operation.

- Pooling layer

CNNs often use the pooling layer operation after convolution layers to reduce dimension, also known as subsampling or downsampling. The pooling layer's hyperparameters represent the filter size and strides. Max pooling and average pooling are the two common types of pooling layer.

- Fully Connected layer

Following several convolution and pooling layers, the FC takes the convolution/pooling output and predicts the best label to represent the image by giving final probabilities for each label.

The CNN has a hierarchical organizational structure that begins with the most basic. The first layer of a CNN recognizes fundamental properties including horizontal, vertical, and diagonal edges. The first layer's output is fed into the next layer, which extracts more complicated properties such as corners and edge combinations. As you progress deeper into the convolutional neural network, the layers begin to recognize higher-level characteristics such as objects, faces, and more. The most typical CNN designs combine a few convolutional layers. It is followed by the pooling layer. From the literature [95] various CNN architecture are proposed LeNet5, AlexNet, VGGNet, MobileNet, DenseNet-121 ResNet, and GoogleNet, each architecture is characterized by different convolution, pooling, and fully connected layers. Different CNN architectures have been widely exploited to classify plants, and promising results have been recorded compared to other techniques. An overview of some relevant works is presented below.

In [96] the authors propose a fine-grained plant leaf classification approach based on deep model fusion, the basic idea is to use two-level CNNs (Google-net architecture) to implement hierarchical categorization techniques. Using pre-trained CNNs on ImageNet and finetune it to plant classification problem (transfer learning), the merging of global and patch-based characteristics is conducted at each hierarchical level (genus and species). The hierarchical levels are fused using a coarse-to-fine method, which means that the predicted coarse categories (genus) are utilized to determine which subordinate category would be evaluated during the fine prediction (species), transfer learning and data augmentation approaches are used to solve the problem of an unbalanced dataset. The test was carried on the well-known dataset the approach produced good results, with an accuracy of 86%. The dual deep learning architecture (DDLA) method was presented by authors in [97]. DDLA is made up of two CNN architectures: (Mobile-Net and DenseNet-121) for feature extraction, and numerous machine learning algorithms for classification. The proposed method (DDLA + LR) achieved higher accuracies for both standard and custom datasets in all of the tests.

In [71] design a new hybrid feature extraction models for plant identification. The authors tried to figure out how CNN learns features directly from the raw representations of an input image. Their major finding was that veins, rather than outline shape, are the most representative characteristics. Two datasets (D1, D2) are used to evaluate the experiments, with D1 representing the whole image and (D2) leaf patches (the leaf image is rotated with 7 different orientations). An accuracy of more than 97%, 99%, and 99% is achieved for datasets. In [98] evaluated how certain factors, such as batch size and iteration count, affected the performance of several deep learning architectures, including Google-Net, Alex-Net, and VGG-Net. They discovered that the number of iterations is the most important factor affecting fine-tuning performance, then data enhancement coming next. In [99] by using vein morphological features, the authors exploit deep learning to identify plant. They first eliminated color information by segmenting veins using Hit or UHMT techniques, and then trained a CNN to recognize them using a centered patch of leaf vein pictures by crooping them at the center to reduce the impact of the leaf shape. In [100] propose combining deep learning features of leaves from various sections of soybean plants to achieve precise species recognition. The deep learning features of triplet leaf image patterns composed of leaves from the lower, middle, and top sections of soybean plants are fused together using two methods: distance fusion and classifier fusion. The features are obtained using a pretrained and fine-tuned CNN model. In [101] authors proposed to extract features based on three different CNN models, the extracted features are classified using several ML classifiers. The results indicate, that the ANN classifier and CNN feature extractor produced the best results. Hu et al. [102] suggested an MSF-CNN for leaf detection at various plant scales (MultiScale Fusion Convolutional Neural Network). The approach involves downsampling an input image into numerous low resolution images using a set of bilinear interpolation operations, which are then fed into MSF-CNN to train discriminative features at different depths. Finally, the last layer of MSF-CNN integrates all discriminative features from the input image to generate the final feature for plant species detection.

Siamese Neural Network (SNN)

Siamese networks were invented by [103] at Bell Laboratories to address the problem of signature verification. It is a kind of neural network architecture that comprises two or more similar sub-networks. The similar sub-networks term refer to the fact that they share the same configuration with the same parameters and weights. The updating of parameters is duplicated across both sub-networks. Siamese networks learn to determine the relationship between two or more inputs. They represent each input using a meaningful embedding space in which related objects are clustered together. The training phase's goal is to discover the embedding that assures the similarity function. In the distance layer, the similarity function is determined using various distances such as the Euclidean distance, the L1 distance, and so on. Then, the loss (contastrive loss or binary crossentropy) value is calculated using two input images, or the loss of triplets using three input images. Siamese networks have been used successfully in zero, one, and few-shot learning applications where there is insufficient data. In contrast, SNNs learn a similarity function. As a result, we can train the SNN to determine if two images are identical. This method allows to identify new types of data without having to retrain the network and with only a few images.

A Convolutional Siamese Network for plant species identification is proposed in [104]. A deep learning approach may be challenging to use with small datasets, thus a comparison of Siamese and CNN for plant species recognition with small datasets was conducted to evaluate the networks. Two scenarios are proposed, in the first one, Flavia is used for the training and for testing. In the second scenario, Flavia is used for the training step and the costa reca dataset for the testing step. They reached the conclusion that the Siamese performed better than CNN in terms of computing cost and generalization. In [105] they propose a Siamese Network based on CNN as a feature extraction method to represent images and KNN for classification. A spatial structure optimizer (SSO) method for constructing the metric space is proposed to improve the speed and performance. Good results have been obtained on three leaf datasets. In [106] authors used S-CNN for plant recognition. They proposed a spatial structure using a deep metric. The S-CNN was used to learn an embedding with similar and dissimilar images. A recurrent neural network was used to model the spatial structure. Experimentation indicates that results surpass all other methods.

Auto-Encoder Neural Network (AE)

An Auto-Encoder (AE) [107] is an unsupervised neural network that uses machine learning. It is a type of deep learning system that can execute two tasks at the same time encoding and decoding. It consist of three layer (encoder, code and decoder), and it begins by converting an input image into a limited number of numerical values. Encoding is accomplished by a sequence of layers that begin with numerous variables and gradually decrease in size until they reach a "code" layer. The code layer includes the required number of variables. The decoder layer reverse the encoding operation by progressing a sequence of layers that begin with code and gradually increase in size until they reach an image. During training, the autoencoder is fed a set of images and train to reconstruct them. The purpose of the training is to discover a technique to tune the parameters in the encoder and decoder layers such that the output image matches the input image as closely as feasible by minimizing the reconstruction loss (MSE, BCE and so on).

In [108] the authors propose to classify plants using the convolutional autoencoder for feature extraction and SVM for classification. A reliable result has been achieved. Images are fed directly to the CAE without any preprocessing techniques. In [109] The authors exploit three sparse autoencoders to extract features and a softmax classifier to output classification results. Optimizing SAE parameters represents a good feature representation.

2.6 Datasets

The images used in the plant leaves systems are classified into three types: scans, pseudo-scans, and photos. The scan and pseudo scan categories refer to plant images obtained by scanning and photographing in front of a simplified background, the photo category refers to plants photographed on a natural background. The most of images used in primary research are scans and pseudo-scans, which eliminates the need to be confronted with occlusions or overlaps. Only few of studies exploited images captured in realistic situations with complicated background. From the literature several datasets has been created. In this section we will provide the well-Known datasets.

Swedish leaf dataset: The Swedish leaf dataset was created as part of a collaborative leaf classification study between Linkoping University and the Swedish Museum of Natural History. The dataset includes images of individual leaf scans on a plain background of 15 Swedish tree species, each with 75 leaves (1125 images in total). Because of its significant inter-species similarity, this dataset is regarded as extremely difficult [127]. The dataset is available for download at http://www.cvl.isy.liu.se/en/research.

Flavia dataset: The leaves of the Flavia dataset were collected from the Nanjing University campus and the Sun Yat-Sen Arboretum in Nanking, China. The majority of these images are of common plants in China's Yangtze Delta. This collection includes 1907 leaf photos from 32 different species, ranging from 50 to 77 images per species. Scanners or digital cameras were used to capture images of the leaves on a white background. The isolated leaf just exposes the blades without petioles. The dataset is available for download at (http://flavia.sourceforge.net/).

ImageCLEF11 and ImageCLEF12 leaf dataset: This dataset was gathered from the French Mediterranean region and developed as part of the Pl@ntNet project. Image-CLEF is one of the most challenging datasets due to its richness in terms of categories of the leaf (compound/simple), species, and (variability/similarity) between (intra/inter) species, in addition to the differences in the acquisition level in terms of period, location, and person. Images taken in 2011 belonged to 71 tree species, which grew to 126 species in 2012. ImageCLEF11 contains 6436 images organized into three categories: scans (48%), scan-like photos or pseudo-scans (14%), and natural photos (38%). The ImageCLEF12 dataset contains 11,572 images organized into three categories: scans (57 %), scan-like photos (24%), and natural photos (19%). Both datasets are free to download from http://www.imageclef.org/.

Leafsnap dataset: Leaf images of 185 tree species from the northeastern United States are included in the Leaf-snap dataset. The images are obtained from two sources and are supplemented by segmentation data. The first source is a collection of 23,147 high-quality lab pictures of pressed leaves from the Smithsonian. These photos are available in both controlled backlit and front-lit formats, with multiple examples per species. The second collection consists of 7719 field photographs collected in outdoor settings with mobile devices (mainly iPhones). The sharpness, noise, illumination patterns, shadows, and other characteristics of these photos vary greatly. The dataset is available for download at http://leafsnap.com/dataset/.

ICL dataset: In the ICL dataset, there are 220 plant species with 26 to 1078 unique leaf photos per species (17,032 images in total). At Hefei Botanical Garden (Heifei), the leaves were gathered. The capital is provinced by members from the local Intelligent Computing Laboratory (ICL) of the Institute of Intelligent Machines, China. Before scanning or photographing the leaves on a plain background, all of the leafstalks were removed. The dataset is available for download at www.intelengine.cn/English/dataset.

2.7 Conclusion

In this paper, we have given an overview of the most existing methods and datasets that have been proposed and exploited in the leave classification system. From the literature, two main approaches have been considered: plant classification based on hand-designed features using a classifier and deep learning strategies. From this study, we have concluded some notes such that:

For the first category, shapes are the most useful features. Veins are another discriminative feature, but due to the extraction difficulties, they were discarded by many researchers. The choice of attributes is in any case very important in machine learning, and the performance depends greatly on the relevance of the descriptors selected to represent the objects of interest. Relatively speaking, the generic hand-crafted features are designed for all types of objects their advantages consist of being simple and rapid. However, they are not always sufficient to provide accurate identifications, mainly due to the "semantic gap" between such representations and high-level semantics. The high inter-class and low intra-class similarities that some species exhibit in terms of certain characteristics that has conducted some researchers to propose domain-specific features.

Domain-specific representations consist of automatic approaches defined by botanists. A set of leaf semantic characters has been defined to differentiate the leaves, including lobes, arrangement, leaf partition (apical, basal), margin of the leaf, veins, etc. However, in the literature, very little attention has been paid to making automatic domain-specific representations distinctions between different species. One of the major drawbacks is the difficulty of automatic discriminant part extraction. For example, the apex (tip) and base of a leaf may be difficult to extract from a lobe, and also the insertion point's appearance (where the petiole, or leaf stalk, meets the leaf blade) may vary greatly depending on the base angle and how the petiole has been cut during specimen preparation. The difficulty of vein extraction and various other factors makes the process difficult.

Attribute selection approaches or dimensionality reduction techniques such as principal component analysis are frequently provided to give the classifier with the most relevant data as input. However, attempting to benefit from the advantages of classifiers by combining them is another aspect that has been successfully utilized in various domains ranging from face detection, medicine diagnosis, handwriting recognition [110], and many others. But in the litterature only a few researchers in the domain of plant classification consider this aspect.

Despite the advancements reached by deep learning in plant recognition, most techniques use it as a feature extractor. DL has several properties that may be adopted to improve and provide reliable result in plant identification systems.

Furthermore, according to the literature most approaches consider plant identification as a flat classification issue, taking advantage of the hierarchical plant organization may serve to accelerate and simplify identification by reducing inter and intra-species problems.

Various datasets have recently been built throughout the world; these datasets are created by researchers based on their study objectives and their own criteria as a result, the variety of plants represented in those datasets are limited and unrepresentative. Relatively speaking those databases are sensitive to regional constraints and suffer from the lack of uniformity rule. As a result, a completely representational, consistent, and universally agreed-upon standard database or dataset should be established in the future.

Chapter3

3 Plant species identification using computer vision techniques

Contents

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Plants species identification using computer vision techniques

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Abstract: Plants are quite important component in our ecosystem. Botanists need to identify plants type for different targets, for example distinguishing the ones which can be used for medical purposes. Traditionally, botanists identify plants manually by using cellular and biological characteristics, which is, in fact, a tedious and time consuming process. Therefore, designing an automatic system, which is capable to identify the different types of plants, is highly recommended. In this paper, we propose a fully automatic method for leaves classification based on computer vision techniques. Instead of extracting the cellular characteristics of plants, our proposed method recognize the type of the plant from the visual features i.e., characteristics which is extracted from a leaf image. The used features include the leaf length, width and diameter. The proposed method is fully automatic, as it doesn't require any human intervention. In addition, it allows persons who are not familiar with the biology domain to recognize the plants type. To prove the efficiency of the proposed system, we conduct experiments on the Flavia dataset which assembles 1907 leaf images of 32 types of plants. Experimental results show promising results and an accuracy of 96% has been reached.

Keywords: plant recognition, morphological features, texture Glcm.

3.1 Introduction

Plants are the backbone of life on the earth and an essential resource for human well being. They are considered as the first living organism born on the earth [111]. Plants play a decisive role in providing clean air, food, medicine and oxygen. They significantly contribute in protecting and maintaining our environment. In the nature, there exist about 3 million species of plants, each with specific characteristics [1]. Identifying plants type is an extremely important task for botanists and scientists from the related fields as well. This is because certain plants are useful for the medical purposes, whereas certain others may be harmful as they can cause diseases or even lead to the death.

Leaves can be used to determine the plant type, as most plant species have unique leaves i.e., a leaf from one type differs from a second from another type in terms of characteristics. Traditionally, botanists and taxonomists adopt different approaches to identify plant species e.g., using molecular biology and cellular characteristics of leaves. However, adopting such approaches for plant identification suffer from serious drawbacks. First, these approaches require performing several critical steps. Second, such approaches are so tedious and time-consuming. Third, only the specialist persons are capable to identify plants, which are, in fact, a serious limitation because identifying plants from no-specialist persons may help in preserving them from the extinction danger. Hence, it is highly recommended, especially with the remarkable development in the computer vision field, to develop anautomatic system for plant species identification.

In the literature, the problem of automatic plants identification has been the subject matter of several studies. Nevertheless, it should be mentioned that most studies have focused on identifying plants using their leaves. The general principle of these studies is to take an image for the plant leaf, then extract the visual features i.e., characteristics of the leaf. After that, computer vision algorithms are applied to determine the plant type. For instance, in [91] visual features of leaves have been combined with Random Forest (RF) and Linear Discriminant Analysis (LDA) classifiers to identify 30 plant species. Similarly, in [112], an Artificial Neural Networks (ANN) classifier has been trained to identify 12 plant species. [61] Have focused on identifying the medicinal plants such as herbs, shrubs and trees based on NN and Support Vector Machine (SVM) classifiers. In our work, however, we use simple yet efficient techniques for plant identification.

In this paper, we develop and design a fully automatic method for plant identification on the basis of leaves images. For a given plant to be identified, we extract the visual features from the leaf image. The visual features include the shape features such as area, perimeter, and diameter. In addition, because leaves of different species may differ in terms of texture, we use the Gray Level Co-occurrence Matrix (GLCM) as a texture feature. Then, we use the K-Nearest Neighbor (KNN) classifier to identify the plant type. The proposed method presents multitude advantages: it is fully automatic and it doesn’t require any human assistance. Beside, no cellular characteristics are needed for identification, and only the visual features are used. In addition, it allows the ordinary persons (i.e., no-specialist) to identify plant species, which may help in preserving plants from the extinction danger. Moreover, it is capable to perform the identification process in a fraction of second, as shown in the experiments. Experimental results, carried out on the Flavia dataset, have demonstrated the efficiency of our method.

The remainder of this paper is organized as follows Section 2 describes shape and texture descriptors present in our method. Section3 show the experimentation on a well known dataset. Section 4 presents conclusion.

3.2 Proposed approach

In this section, we explain our proposed method for leaf identification which is based on morphological and GLCM features. It takes as an input a color image (i.e., image in RGB space), and gives as an output the class to which this image belongs. The method consists in four main stages namely, preprocessing, feature extraction, features combination and classification stage. Each of these stages will be detailed in the following four sub-sections. Figure 3.1 shows the general scheme of our proposed method.

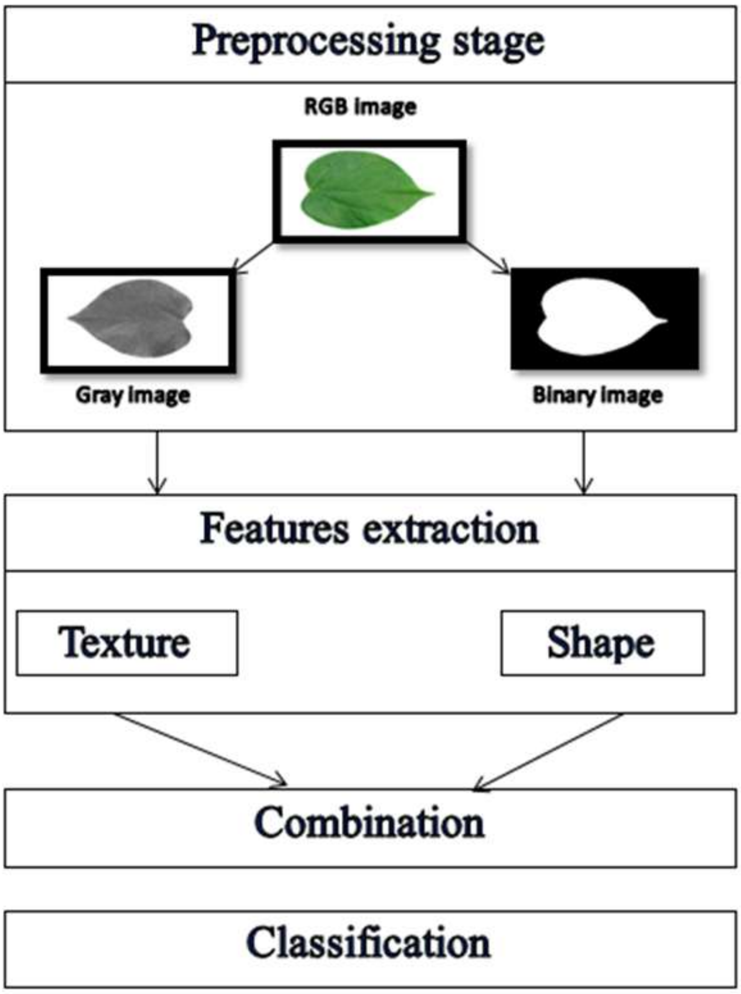

Figure 3.1: General scheme of our method.

3.2.1 Preprocessing

The preprocessing stage is fundamental in most systems. This stage is, generally, responsible for applying a set of treatment (e.g., noise reduction, rotation, transformation, etc.) on the image before employing it for information extraction. We devote this stage to two main processes, the first one is image minimization while the second one is gray-level image transformation. Thus, this stage gives as output two images, resulted from the original image, which are: gray-level image and binary image.

3.2.2 Features extraction

In this stage and having obtained the gray-level and the binary image, we extract a set of shape and texture features, such that, shape features are extracted from the binary image while the texture features are extracted from the gray level image.

- **Shape features**

Morphological features are shape features that consist in the extraction of the basic geometrical properties [113] of the leaf such as: diameter, area, perimeter, etc.

Figure 3.2 shows an example of some geometrical features that can be extracted from a leaf image. In our method, we extract a set of geometrical features including, diameter, area, major axes length, minor axes length, and perimeter. In addition and based on these features, we extract another set of digital morphological features, as described in [113] [114], namely, aspect ratio, Perimeter Ratio of Physiological, Perimeter Ratio of Diameter, rectangularity, narrow factor, circularity and solidity.

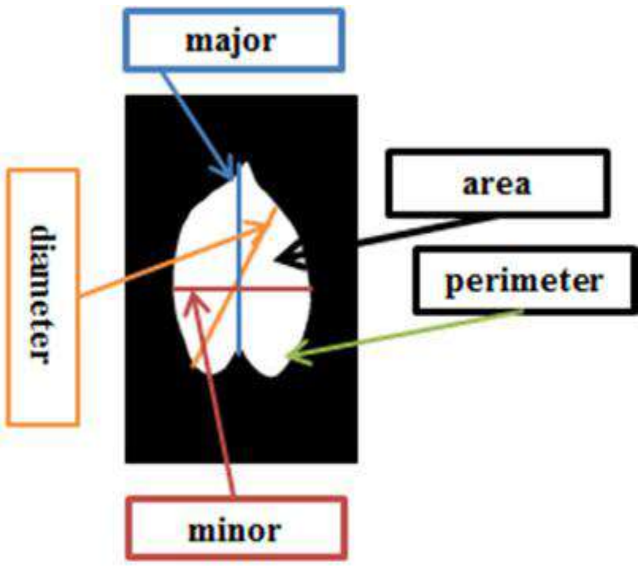

Figure 3.2 : Basic geometrical features.

- Diameter: (D) is the longest distance between two points of the leaf contour.

- Area: (A) is the number of the pixel count of the leaf area.
- Major axis length: (LP) is the distance between two terminals points orthogonal to minor axis length.
- Minor axis length: (WD) is the longest distance orthogonal to major axis length.
- Perimeter: (P) the number of pixels at the margin of the leaf.
- Aspect Ratio: is defined as the ratio of major axis length LP to minor axis length WP. It is also called Eccentricity or Slimness. $AspectRatio = LP/WP$.
- Perimeter Ratio of Physiological length & width: this features is the ratio of perimeter leaf and the sum of major and minor axis length $PRPW = P/(LP + WP)$.
- Perimeter Ratio of Diameter: it is the ratio of perimeter to the diameter $PRD = P/D$.
- Rectangularity: The similarity between the leaf and a rectangle, given by $(Lp * Wp)/A$.
- Narrow Factor: the ratio of the diameter D and length Lp, thus D/Lp.
- Circularity: The ratio involving area A of the leaf and the square of its perimeter P given by $C = 4\pi A/p^2$.
- Solidity: The ratio between A the area of the leaf and Ach the area of a convex hull given by A/Ach.

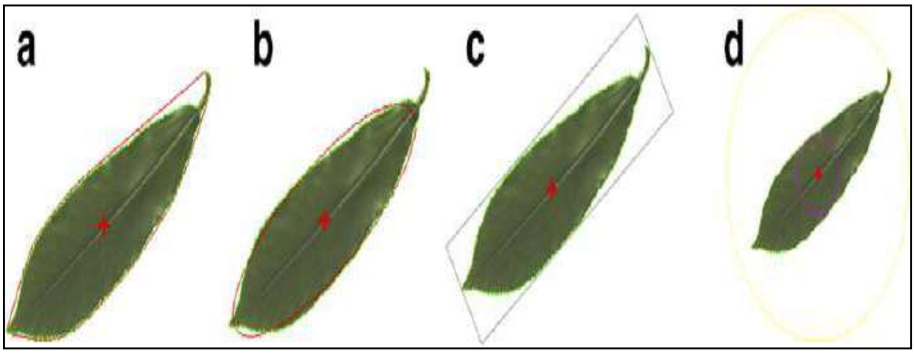

Figure 3.3 : (a) Convex hull, (b) Form ellipse, (c) Rectangularity, (d) Circularity.

- **Texture features:**

Veins Figure 3.4 are one of the most used characteristics to distinguish between leaves. Therefore, we have tried to employ such an informative characteristic in our method to describe leaves. We therefore extract a set of texture features from grey-level leaf images.

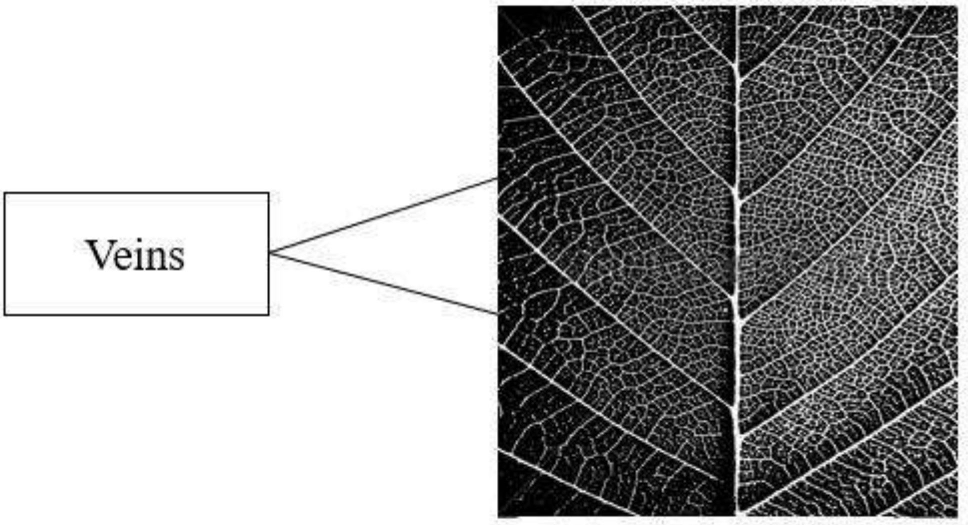

Figure 3.4 : Leaf veins.

These textures features come in form of second order statistical moments extracted from a GLCM [51]. This is generated co-occurrence frequency of different gray-level pairs within the image. In simpler words, let us suppose that we extract a GLCM *M* from a gray-level leaf image. Then, each element $M\ (i, j)$ represents the frequency of a gray-level *j* that appears at a given offset $(\Delta x, \Delta y)$ from a grey level i. For a given image I and offset (Δx, Δy), the GLCM could be extracted using the next formula (1).

$$M(i,j) = \sum_{p=1}^{N}\sum_{q=1}^{M}\begin{cases}1, & \text{if } I(p,q) = i \text{ and } I(p+\Delta x, q+\Delta y) = j \\ 0, & \text{otherwise}\end{cases} \qquad (1)$$

There are many features that can be extracted from the GLCM including second moment, contrast, correlation, variance, inverse different moment, sum average, sum variance, sum entropy, entropy, difference variance, difference entropy, maximal correlation cofficient and other mesures of correlation. However, in our method we use only the form most uncorrelated ones to describe texture which are, Contrast, Homogeneity, Correlation and Energy.

Contrast: it is used to measure the local grey level variation.

Homogeneity: It measures the uniformity of the non-zero values in the GLCM matrix, it measure the spatial autocorrelation.

Correlation: It is a measure of linear dependency.

Energy: It explains how uniform the texture is.

- **Features combination**

After applying stage 2 (i.e., feature extraction) the results will be two vectors, one for shape and the other for texture features. There are several techniques of features combinations. One may think to establish weights that determine the importance of each feature. However and in order to keep things simple, we simply concatenate these two feature vectors (i.e., shape and texture feature) without assigning any weights because the values of the two features are in the same range. This means that all features are important as the same.

3.2.3 Classification

In this final stage, feature vectors, which are extracted then combined in previous stages, are compared in order to identify the appropriate class of a given leaf. This stage is composed of two sub-stages which are learning and recognition.

- **Learning stage**

The aim of this sub-stage is to train our method so it can distanguish the visiual propoerties of the different leaf class. It takes as input a number of images per each class and then extract feature vectors from each as shown in Figure 3.5. Then, the extracted features are served to Knn classifier [82] [115] to generate our trained model. This model will be used later on to identify to which class belongs a given new leaf image.

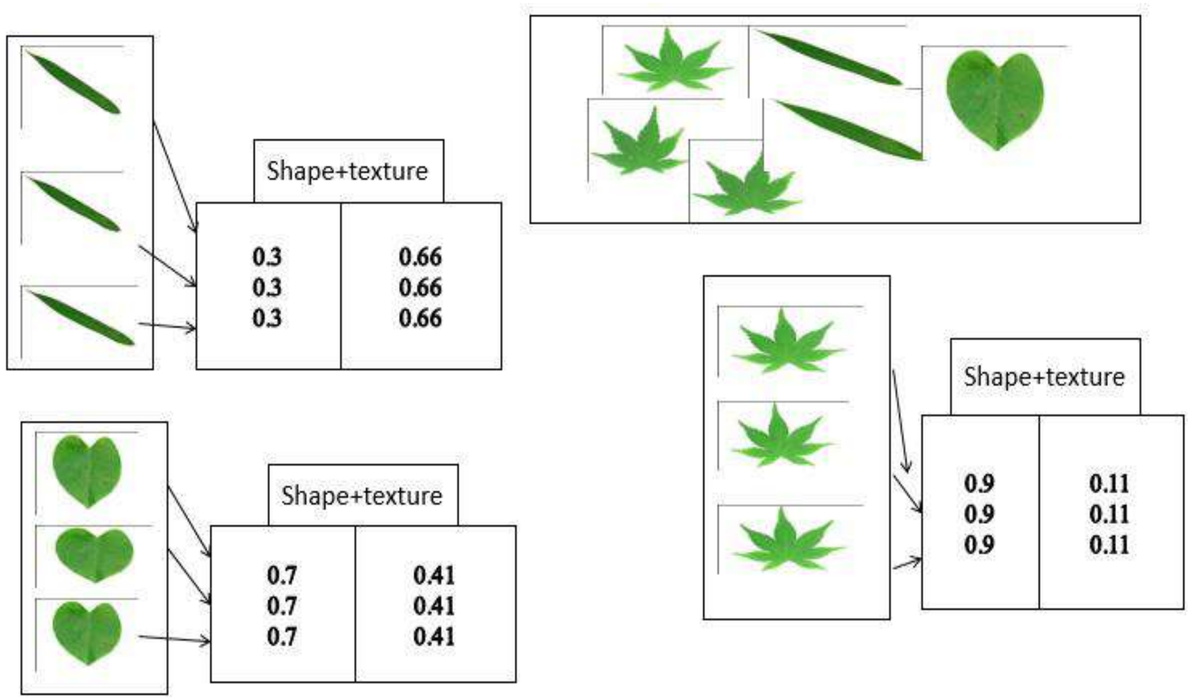

Figure 3.5 : Training stage.

- **Recognition**

Because a few dimentsion vectors have been obtained in the feature extraction step, in this stage the pre-trained KNN model in order to classify data has been used. For a given test leaf sample, the appropriate class. This is done by calculating the similarity between the feature vector of the given test image and those extracted from the training image. The similarity could be extracted using the next formula (2).

$$d(\mathbf{x}_r, \mathbf{x}_s) = \left[\sum_{i=1}^{p} c_i (x_{ri} - x_{si})^2 \right]^{1/2} . \qquad (2)$$

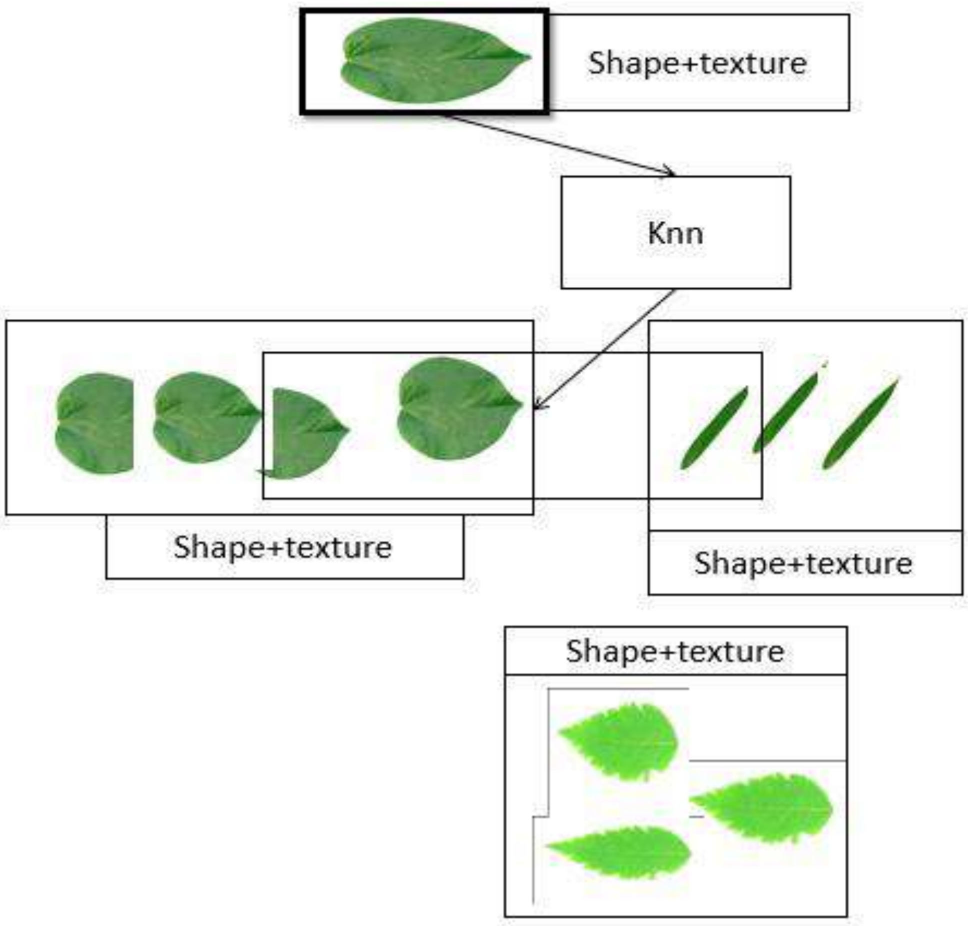

Figure 3.6: Recognition stage.

3.3 Experimental results

In order to evaluate our method we have used the Flavia dataset. Flavia is well-known dataset [111] that contains 32 classes with a total of 1907 images. Figure 3.7 shows representative samples from this dataset.

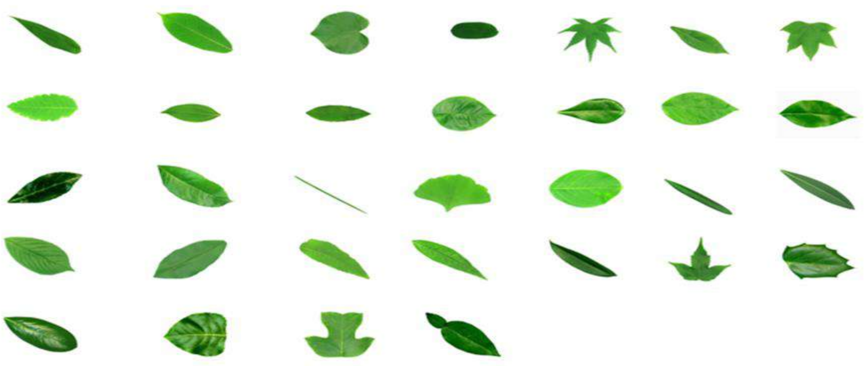

Figure 3.7: Representative samples of each class from the Flavia dataset.

We devote 2/3 of the dataset to train our method, whereas the remaining is devoted to test our method and report its accuracy. Our method has shown high recognition accuracy by recognizing overall 96% of the test images. It even yields for some class (i.e., species) recognition rate of 100%.

From Table 3.1, we notice that the combination of two features shape and texture has yielded better recognition rate than one feature. Texture features have outperformed shape features because of the similarity shape of some species.

Table 3.1: Accuracy over all species yielded by each combination.

Feature	Accuracy
Morphological	66%
Glcm	94%
Morphological+glcm	96%

3.4 Conclusion

Plants present an essential resource for human life such as food and medicine. Therefore an automatic system is needed to identify different plant species. In this paper we have proposed a method based on morphological features in order to capture shape properties of plants. Because of some species are shapes alike, we have included also GLCM texture feature to capture internal structure of leaf veins. Experimental evaluation shows that our method yields excellent results with overall accuracy of 96% and 100% for some species and in quickly time.

Chapter 4

4 Plant Leaves Classification Using a Modified Multi Scale Triangular Distance Matrix

Contents

Plant Leaves Classification Using a Modified Multi Scale Triangular Distance Matrix

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Abstract

An automated plant species identification system could help botanists and laymen in quickly recognizing plant species. Leaf shape is commonly used in automatic plant recognition since it carries many features and can be easily recorded using low-cost equipment. The shape of leaves varies along the margin, as well as at the apex, base, and around the center. In this paper, we present a modified shape feature (MMTCD) that takes into account points from discriminant portions rather than the entire contour and captures both global and local shape characteristics. To classify the feature set, a random forest classifier is used. The proposed method is validated using the well-known Flavia dataset. The results demonstrate that the proposed solution is quite efficient in terms of accuracy, time, and memory space.

Keywords: plant leaves recognition, leaf shape, apex, base, Random forest.

4.1 Introduction

Plant recognition is a matter of interest for scientists as well as laymen. It is critical in many areas of human endeavor, including agronomy, conservation, environmental impact, natural product, medicine discovery, and other applied domains. Accelerating and making this task more accessible to non-experts would be extremely beneficial, thanks to advances in science and technology. Botanists can now use computer vision technologies to help them identify plants. Automatic plant species identification is rapid, inexpensive and, accurate as well. There are over 3 million plant species in nature, each having unique traits [1]. Plant identification is a significant topic for botanists and other scientists working in related fields. Traditional field guides or identification keys are much more difficult to use and need significantly more time to get the same result, even for botanists and professionals. Unfortunately, most plants only blossom and yield fruit for a very short period of time each year (from few days to few weeks). It is usually necessary in such circumstances to investigate any dried or dead flowers or fruits that may be present. When it comes to vegetative components, it is common practice to inspect the leaves first. Color, shape, texture, morphology, and venation structure are the leaf features that have been studied. Color is not considered as a discriminative characteristic since it can change over time. Shapes and texture characteristics are the most discriminant leaf traits, however owing to the difficulties of acquiring texture, some studies have had to discard it in preference of shape because it contains a lot of information and is easy to capture. In [26] authors classified shape into contour-based approaches and region-based methods based on shape features collected from the target's entire region or contour only. For various reasons, research on contour-based shape identification [28] has been more active in the recent decade than on region-based [26] that is because people are thought to be capable of distinguishing different shapes from only the contour, Furthermore, in many shape applications, the contour of the shape is all what it matters. Various categories emerge from the literature under contour shape characteristics, one of which is spatial interactions between contour points. The main idea behind this category is to sample a series of equidistant points from the contour, from which a set of features must be derived. The most commonly mentioned features are (shape context, inner shape context, MDM, CCD, and so on). If we take a look at leaf contour shape as a distinguishing feature, we can observe that specific areas differ from one species to another. In this paper, we have proposed a modified feature and in the contrast to the literature, our methods considered points only from discriminant parts apex, base, and center rather than all the entire contour point. According to the experimental results, our methods outperform state-of-the-art methods, the rest of the paper is organized as follows. Section 2 discusses related works. Section 3 describes in detail the proposed modified triangular characteristics. Section 4 contains the experimental outcomes of our method. Finally, in Section 5, we provide our conclusion.

4.2 Related work

A large number of studies have been performed during the past few years to automatically identify the plant type in a given image. Since the shape of leaves provides abundant visual information. In this section, will mostly study relevant works on shape-based methods.

Regarding to features methods that has been proposed in the plant recognition domain, and according to [24, 25] leaf features are defined into two categories: general visual features and domain related features. General visual features, such as color, texture and shape features are not designed for leaf images only, but rather for all types of images regardless the content. Whereas, domain-related visual features are specified for leaf images, they are based on the morphology of the leaf, such as shape, dent, vein, margin, and so on. For the first category we mention as instance Ling et al [29] used the inner-distance shape context (IDSC) descriptor to identify plant leaves, good results has been achieved in term of classifition. However, because the method uses dynamic programming to determine shape dissimilarity, its temporal complexity is very significant. In [32] Hu et al. introduced the multiscale distance matrix (MDM), a contour-based shape descriptor for rapid plant leaf identification. It captured the geometric structure of the shape by using a matrix of pairwise distances between points collected on the edge of a leaf. In comparison to other contour methods, MDM without (DP) is seen to be a particularly successful method. Wang et al. presented a technique in [34] that employs a multi-scale arch height (MARCH), hierarchical arch height characteristics at K-scale are extracted from each contour point it captures concave and convex features and provides a coarse-to-fine shape description of the leaf, the 1-Nearest-Neighbor classifier was used to determine the recognition rate and a prototype system for online plant leaf identification was created for usage on a mobile platform. In [116] proposed utilizing two matrices to describe the leaf contour. The first is a sign matrix that is used to extract convex/concave features, and the second is a triangle center distance that is used to extract the contour's spatial characteristics. By integrating leaf shape and margin characteristics, Zhang et al. [117] presented a novel plant identification technique. Simultaneously, they used a number of multi-grained fusion techniques that integrate the margin feature with the shape information to create a more accurate depiction of a leaf. In [118], Kadir et al. develop plant identification systems Zernike moments were combined with other features: geometric features, color moments and gray-level co-occurrence matrix (GLCM), the Zernike Moments have a prospect as features in leaf identification systems when they are combined with other features. Alghtouth the effectiveness of the generic features but, relatively speaking, those visual approaches are created for all sorts of items. Their advantages include being simple and quick. However, due to a "semantic gap" between such representations and high-level semantics, they are not always adequate to provide correct identifications. The great inter-class and low intra-class similarity that certain species exhibit in terms of particular traits has led researchers to focus on specific aspects. Domain-specific representations consist of automatic approaches defined by botanists. Set of leaf semantic characteristics has been established, including lobes, arrangement, leaf partition (apical, basal), leaf border, veins, and so on. The automated extraction and discrimination of botanical information has become a major focus of current computer-assisted research. For instance, Mzoughi et al [67] define the approach that is based on the computation of features from a specific point of the contour such that (Maxima (concave, convex) and inflection points), the features are mainly focused on the frequency and the spatial distribution of maxima concave, maxima convex and inflection points. The experiment was carried out on public dataset plant clef 2011. A method that relies on leaf margins as descriptors are proposed in [69]. Tooth and pits along the leaf margin are extracted by the method CSS, the descriptor represents tooth and pits as sequences such that (size, curvature (positive or negative), vertical position according to the position of apex and base).for the classification NN is used. In the literature, very little attention has been paid to make automatic Domain-specific representations as a distinction between different types of leaves, one of the main major obstacle consist in the extraction of discriminant parts (apex tips veins etc) automatically.

4.3 Proposed method

In this section we present our proposed system .We begin by introducing proposed features, followed by a brief overview of prospective classifiers.

1. Feature:

The proposed feature is based on the idea of MTCD [119] and is intended to gather information about local leaf shapes. The MTCD shape contour descriptors, according to the literature, fall within the category based on Multi-scale representations. Its fundamental concept is to sample an equidistant point from the contour, and then a number of features must be extracted from the points at multiple levels by capturing local and global features from low- to high-resolution scales. The most often mentioned features include (TOA, MDM, TAR, etc.). Leaf shape differ from one species to another in different parts (margin, apex, base and centre), in order to gather this usfuel information and unlike previous contour shape methods, in our approach we collected features solely from discriminative portions of leaves rather than the entire leaf. The concavity and convexity of each contour point in the discriminant portion can be measured on various scales. Figure 4.1 depicts the distinguishing leaf components (base, apex, and apex).

Figure 4.1: Different parts of leaf.

In our method, we first rotate the leaf picture in a vertical position, and then, after identifying the base, apex, and center points using the major axis length, we sampled the same number of points around the mentioned points in an equidistance and counterclockwise manner for each leaf image. Following the point location from the discriminat part, we used the same MTCD principle [119].When the contour is traversed in counter clock-wise direction, for straight, concave, and convex boundaries.In MTCD For each point (x_i, y_i) a triangle is constructed, by considering the point P_i and the two neighboring points (x_{i-t}, y_{i-t}) and (x_{i+t}, y_{i+t}), where $i \in [1, N], t \in [1, T]$ $(T = [N-1/2]$, T presents the number of scales), then for each triangle the centroid point is determined C_{it}, = (x_{cit}, y_{cit}), where($i \in [1, N], t \in [1, T]$($T = [N-1/2]$)). For each point P_i of the contour of a leaf, there are T triangles. Therefore, the MTCD shape descriptor of this point Pi can be expressed by using the following expression:

$$MTCD(S) = (MTCD(P_i), \dots \dots \dots \dots .., MTCD(P_N))$$

Where $TCD(p_i, c_{it}) = \sqrt{(x_i - x_{cit})^2 + (y_i - y_{cit})^2}$

$$\text{MTCD} = \begin{pmatrix} TCD(p_1, c_{11}) & \dots\dots & TCD(p_N, c_{N1}) \\ \dots & \dots. & \dots.. \\ TCD(p_1, c_{1T}) & \dots.. & TCD(p_N, c_{N1}) \end{pmatrix}$$

By dividing MTCD(S) by the maximum absolute value of each row, the shape descriptor becomes scale invariant.

2. Classification:

In order to classify plant using MMTDC we have explored the Random Forest classifier **RF** is a machine learning classification approach that has proven to be quite successful in plant recognition [120]. A vast number of datasets may be classified using this method. A Random Forest [79]is a collection of decision trees in which N training samples are randomly selected and each tree is trained with replacement using these N samples. Random Forest's pseudocode is:

1. K features from m are chosen at random. (k<<m)

2. Among the supplied K features, the best split point node d is computed.

3. The daughter nodes are separated using the best split.

4. Unless a number I of nodes are reached, continue steps 1 through 4.

Steps 1–4 are repeated to make a number n of trees.

4.4 Experimental Results

The evaluation of the used approach has been carried out on Flavia dataset [113] **.** Flavia is a public leaf dataset that can be freely downloaded from the web. It has 1907 leaf images categorized into 32 different species with the number of samples in each ranging from 50 to 77. Figure 4.2 shows representative samples from Flavia.

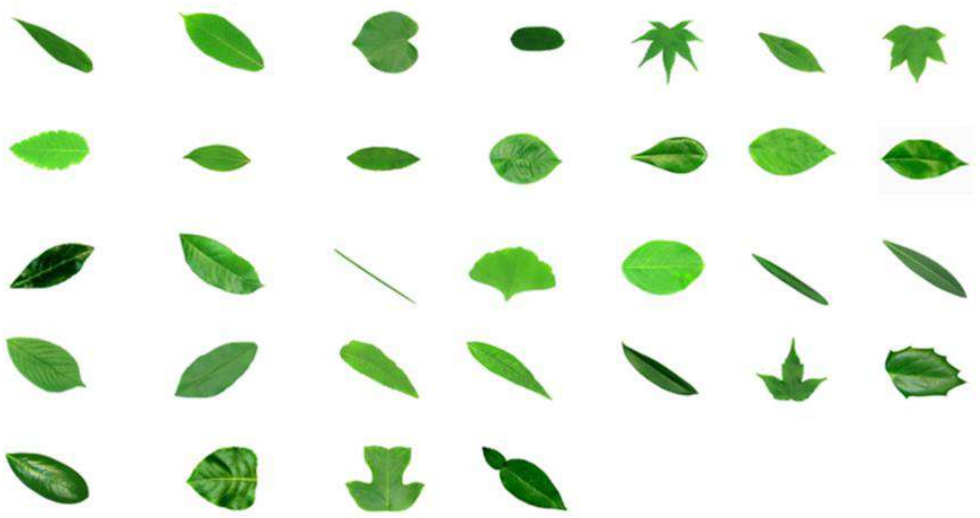

Figure 4.2: Represntative Sample of flavia dataset.

- **Results**

In this part, we will compare the approach we used to relevant publications on leaf categorization. We used the identical dataset arrangement as in [119] to do this. We select 10 samples from each spcies for testing and the rest images from each species are used for training, while the remaining samples are used for testing. Table 4.1 present accuracy of our proposed method MMTCD (Modified Multiscale Triangular Centroid Distance) and MDM (Multi Scale Distance Matrix).

In order to evaluate our proposed feature, we have to rely on accuracy for the overall performance.

$$Accuracy(\%) = \frac{Number\ of\ correctly\ classefied\ test\ images}{Number\ of\ total\ test\ images} \times 100$$

Table 4.1 : Accuracy of the proposed method (MMTCD).

Methods	Accuracy
MDM	88%
MMTCD	89%

As we can see, our adopted approach, that consider points from discriminat parts, has outperformed the method that considers points from all parts. Moreover, we can see that MDM with 1238 size features consumes more time and memory compared to only 123 size features of our feature.

4.5 Conclusion

Plants provide important resources for human survival, including food and medicine. As a result, an automated method is needed to recognize various plant species. According to the literature, all of the shape characteristics that are behind multi scale representation need time and memory (high feature size) since it takes into account all points from all regions on the leaf. Randomly points sampled from various parts may have a noisy characteristic. Develoing a mobile plant application need a compact features. Leaves have discriminative sections (base, apex, and around the center). In this paper, we have presented a modified multi scale triangulare distance features.and our goal in our contribution is the consideration of only points from discriminative a reliable results has been achieved in terms of memory space and accuracy.

Chapter 5

5 Automatic recognition of plant leaves using parallel combination of classifiers

Contents

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Automatic recognition of plant leaves using parallel combination of classifiers

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Abstract. Because they are exploited in many fields such as medicine, agriculture, chemistry and others, plants are of fundamental importance to life on earth. Before it can be used, a plant need to firstly be identified and categorized. However, a manual identification task requires time, and it is not an easy task to do. This is because some plants look visually similar to the human eye, whereas some others may be unknown to it. Therefore, there has been an increasing interest in developing a system that automatically fulfils such tasks fast and accurate. In this paper, we propose an automatic plant classification system based on a parallel combination technique of multiple classifiers. We have consider using three widely known classifiers namely Naïve Bayes (NB), K-Nearest Neighbour (KNN) and Suport Vector Machine (SVM). Our system has been evaluated using the well-known Flavia dataset. It has shown better performances than those obtained using only one classifier.

Keywords: Morphological features, parallel classifiers, leaf classification, plant leaves, image recognition.

5.1 Introduction

Plants play an important role in our life, without them there will be no existence of the earth's ecology. They are widely exploited in our life such as in food, breath, health, and even in industry fields such as medicine, economic, agriculture, and so on. There are millions of plants species, some of them are subject to the danger of extinction [6]. Therefore, there is an urgent need for identifying plant species to prevent this disaster.

Traditionally, botanists classify plants using molecular biology and cellular features of leaves. Nevertheless, this task is very tedious, requires time and need the presence of expertise which is not available in all times. Additionally, an expert on one species or family may be unfamiliar with another. Subsequently, fast and accurate automatic plant identification system is highly needed.

Plants are usually classified using their leaves, stems, fruits or flowers. Leaves seem to be the most suitable parts that can be used to identify a plant. This is due to their availability in all seasons. In addition, leaves flatness makes it easy to be represented by the computer in some 2D.

From the literature, plant identification techniques are a hot topic of research [121]. Authors in [91] have exploited the visual features of leaves in combination with Random Forest (RF) and Linear Discriminant Analysis (LDA) to classify and identify 30 plant species. In [113] a similar technique, but using Artificial Neural Networks (ANN) this time, has been opted for to identify 12 plant species. Pedro et al. [114] have focused on developing a system that can automatically identify medicinal plants such as herbs, shrubs and trees. As a classifier, they use ANN then Support Vector Machine (SVM).

The reader should notice that the former works use only one classifier in their systems. Thus, some other works have tried to improve them by combining and using more than one classifiers in the system. In [122] as instance, authors suggest using a serial combination of two SVMs. Their main idea was to devote one classifier for color features, and the other one for both shape and texture features. Their evaluation has been carried out on a dataset that contains six diseases classes. The system reports an 87.7% accuracy. In [123], authors have used a parallel combination of two classifiers namely, ANN and SVM. The first one was devoted to texture, color and shape features, whereas, then the second one uses shape and texture features. The evaluation has been carried out on a dataset that is composed of six diseases classes and they reported 91.46% accuracy.

In this paper, we introduce a system that parallel combines three classifier namely SVM, NB and KNN. As features, we consider extracting shape features (i.e., morphological features) from the leaves. The evaluation of our system has been accomplished using the well-known Flavia dataset. More details about the proposed system will be given in the next section.

The rest of the paper is organized as follow: section 2 present the architecture of our system and then discuss the used morphological features. In Section 3, we conduct experimentations on the proposed system and report results. Finally, we draw some conclusions.

5.2 Proposed system

In order to achieve a better performance, our system consists in a parallel combination of three classifiers namely SVM, NB and KNN. These classifiers are trained using a set of morphological features that we extract from the leaves. In Figure 5.1, we illustrate a general scheme that resumes the different main stages of our system.

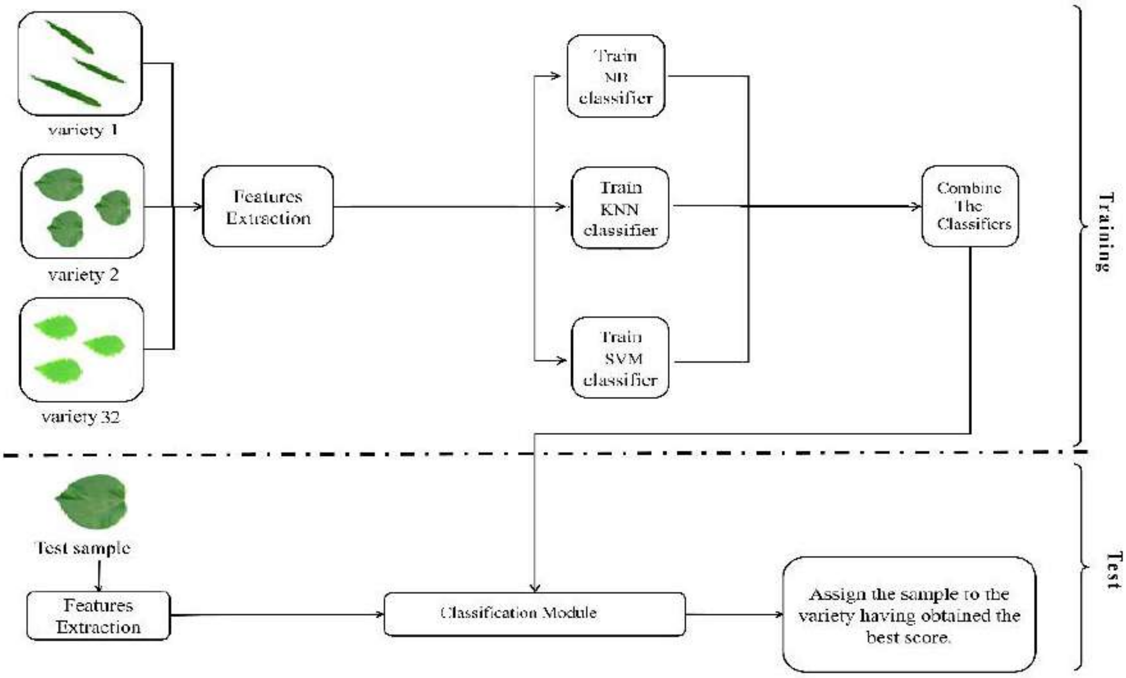

Figure 5.1: Architecture of the proposed system.

5.2.1 Preprocessing

The preprocessing stage is, generally, responsible for applying a set of treatment (e.g., noise reduction, rotation, transformation, etc.) on the image before employing it for features extraction. In our work, we firstly converted the original color images to gray-level then to binary images. Thereafter, a smoothing filter is applied to these binary images to reduce the noise. The steps involved in pre-processing are illustrated in Figure 5.2.

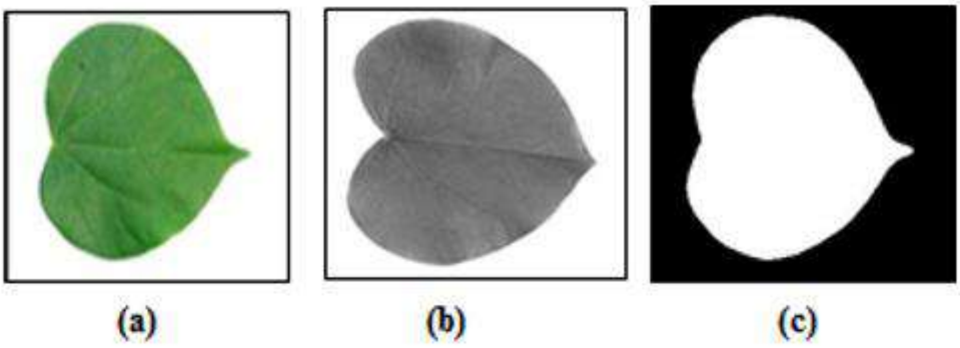

Figure 5.2: Preprocessing stage (a).Rgb image, (b).Gray-level image, (c).Binaryimage.

5.2.2 Features extraction

This stage aims to transform the objects into a vector of numeric values (i.e., feature vector). There are many types of features that can be extracted from an image, such as shape [124], texture [125], and color [126] features.

In this stage and after having the original image transformed into binary, we extract a set of shape features that describe the morphology of a leaf. Morphological features are obtained by extracting the basic geometrical properties [1] of the leaf such as: diameter, area, perimeter, major and minor. Figure 5.3 shows an example of some geometrical features extracted from a leaf image.

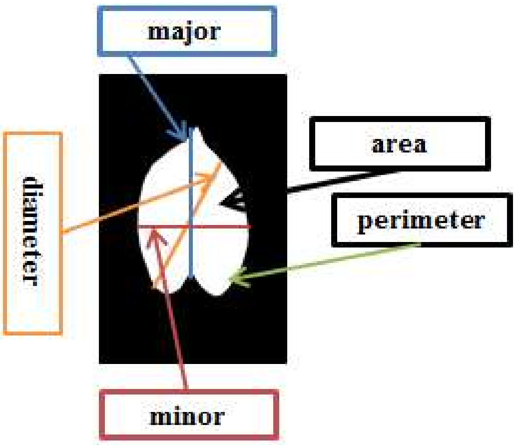

Figure 5.3: Basic geometrical features.

In our method, we extract the following five morphological features:

Diameter: is the longest distance between two points of the leaf contour D.
Area: is the number of pixels that constitute the area of the leaf.
Major axis length: is the distance between two terminal points orthogonal to minor axis length LP.

Minor axis length: is the longest distance orthogonal to major axis length WD.
Perimeter: the number of pixels at the margin of the leaf P.

In addition and based on these features, we extract another set of digital morphological features that were introduced by the authers of [1] [115], which are:.

Aspect Ratio: is defined as the ratio of major axis length LP to minor axis length WP. It is also called Eccentricity or Slimness. It is given by AspectRatio=LP/WP.

Perimeter Ratio of Physiological length & width: this features is the ratio of perimeter leaf and the sum of major and minor axis lentgh, given by PRPW=P/(LP+WP).

Perimeter Ratio of Diameter: it is the ratio of perimeter to the diameter, given by PRD=P/D.

Rectangularity: The similarity between the leaf and a rectangle, given by R=(Lp*Wp)/A.

Narrow Factor: the ratio of the diameter D and length Lp (i.e., NF = D/Lp).

Circularity: The ratio involving the area A of the leaf and the square of its perimeter P, given by $C = 4\pi A/p^2$.

Solidity: The ratio between *A* the area of the leaf and *Ach* the area of a convex hull, given by S = A/Ach. Figure 5.4 shows some of morphological features.

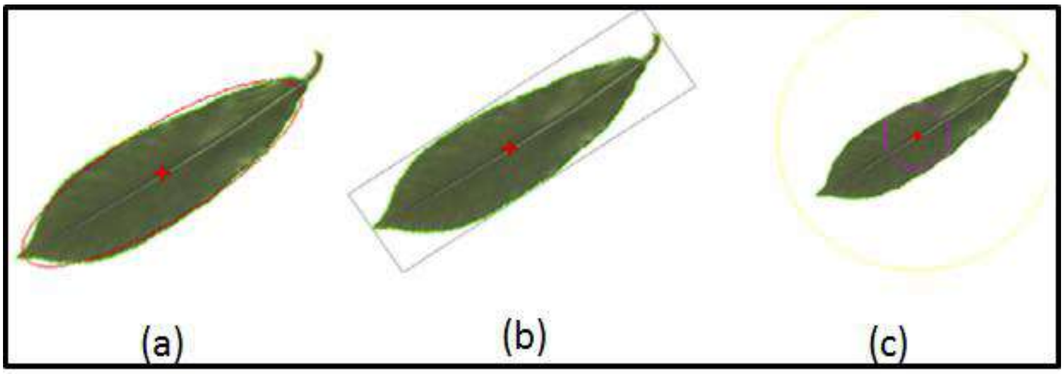

Figure 5.4 : Morphological features. (a). Form ellipse, (b). Rectangularity (c). Circularity.

5.2.3 Classification

Classification or categorization is, generally, the process in which images are recognized, differentiated, and understood. The classifier needs to, firstly, be subjected to a set of labeled data (i.e., training set). Then, test samples will be provided to the classifier in order to recognize them. In our work, a portion of the feature vectors, which are extracted in the previous stage, will be used to train our system that consists in three kinds of classifiers Knn [1, 115], NB[127] and SVM [128]. These three classifiers are combined in parallel. The parallel approach allows the different classifiers to operate independently of each other. The results of each classifier are then merged in order to obtain a higher recognition rate.

- **K-Nearest Neighbor (KNN).**

KNN [1] is a simple yet very effective classification method. For a given test sample *s*, KNN mainly consists in determining the *k* closest training example to this *s*. It then states the class *C* that has the max membership degree to s as a class of s. the similarity could be extracted using the next formula (1).

$$d(x_r, x_s) = [\sum_{i=1}^{P} c_i \, (x_{ri}, x_s i)]^{\frac{1}{2}} \qquad (1)$$

- **Support Vector Machine (SVM).**

SVM is a supervised classifier [74] that has a great effectiveness especially with high dimensional data [128]. Formally, SVM constructs a hyperplane (alt. hyperplanes) that has the highest distance to the nearest training-data point of any class [129].

- **Naive Bayes (NB).**

Naive Bayes classifiers [127] are a family of simple probabilistic classifiers based on applying Bayes' theorem with strong (naive) independence
assumptions between the features [127].

$$P({}^{C}/_{x}) = \frac{\mathrm{P}({}^{\mathrm{X}}/_{c})\mathrm{P(c)}}{\mathrm{P(x)}} \qquad (2)$$

where:

- $P({}^{C}/_{x})$: is the posterior probability of class c (i.e., target) given predictor x (i.e., attributes).
- P(c): is the prior probability of class.
- $\mathrm{P}({}^{X}/_{c})$: is the likelihood, which is the probability of predictor given a class.
- P(x) : is the prior probability of predictor.

Naive Bayes conditional independence assumption, assume that probability of observing the conjunction of attributes is equal to the product of the individual probabilities $p(x_i/c_i)$.

$$\mathrm{C_{nb}} = \mathrm{argmaxP}(\mathrm{c_j}) \prod_{\mathrm{i}} \mathrm{p}(\mathrm{x_i}/\mathrm{c_j}) \qquad (3)$$

- **Combination classifiers**

The main aim of combining classifiers is to improve the accuracy. Several works have been proposed in this context [122]. Classifier combination schemes could be roughly categorized into three main approaches, namely: sequential, parallel and hybrid combination.

1. **Sequential combination:**

The sequential combination consists in placing one classifier after the other. It simpler words, the outcome of one classifier will be the input of another. Such a cascade structure helps to improve the decision taken from the previous step by including reliable samplers or excluding unreliable ones [122].

2. Parallel combination:

In parallel combination, the different classifiers operate independently of each other.Then, the obtained results are fused together, by some method, to produce a final decision [123].

3. Hybrid combination:

The hybrid combination scheme takes the advantages of the two previous schemes (i.e., sequential and parallel combination) in order to reach a more reliable decision. It illustrates the two aspects of the combination which are: in on the one hand reducing all possible classes and in the other hand finding the consensus between all classifiers, in order to reach a final decision [130].

Parallel combination presents several advantages. Regarding other strategies, this one is simple and easy to implement. The calculation time is reduced because all classifiers work in parallel, as well as the possibility of modifying one or more classifiers without affecting the system. In our system, we combine the classifiers in a parallel way and we opted for voting-based methods [131]. In such module, each classifier provides a certain number of votes (i.e., potential classes for a given image). The final decision is then made based on these votes using the following formula:

$$E(x) = \begin{cases} c_i \ si \ \sum_i e(i) = \max\limits_{c_i \in \{1,\dots,M\}} \sum_j e(j) \geq \alpha K \\ \qquad else\ reject \end{cases} \quad (3)$$

Where K is the number of the combined classifiers, α is a threshold that represents the needed number of votes for the same class to be relevant.

Voting-based method could be categorized into two main categories, the simple majority vote and the weighted vote.

In simple majority vote [132], each classifier votes for one class to be relevant to an input image. The final decision will, then, be made regarding the number of votes for each class. The relevant class is the one with the heights number of votes. Although this method is simple and effective, it suffers from the problem of rejection if all classes have the same votes number [133].

On the other hand, the weighted vote method associates each classifier with some coefficient (i.e., weight) that indicates the importance of the corresponding classifier in the combination. Selecting weights for different classifiers is a critical process and highly affects the quality of the results.

To take the advantage of both the former voting methods, we suggest combining them in one module. In our used module, the system tries, firstly, majority vote method. If a conflict occur using the majority vote, then, the system opts for weighted vote method. The following algorithm resumes these two steps.

```
If (DSVM==DKNN==DNb) Then
  FD ← DSVM+DKNN+DNB
Else
  FD ← α DNB + β DKNN+Ω DSVM
Endif
```

5.3 Experimental results

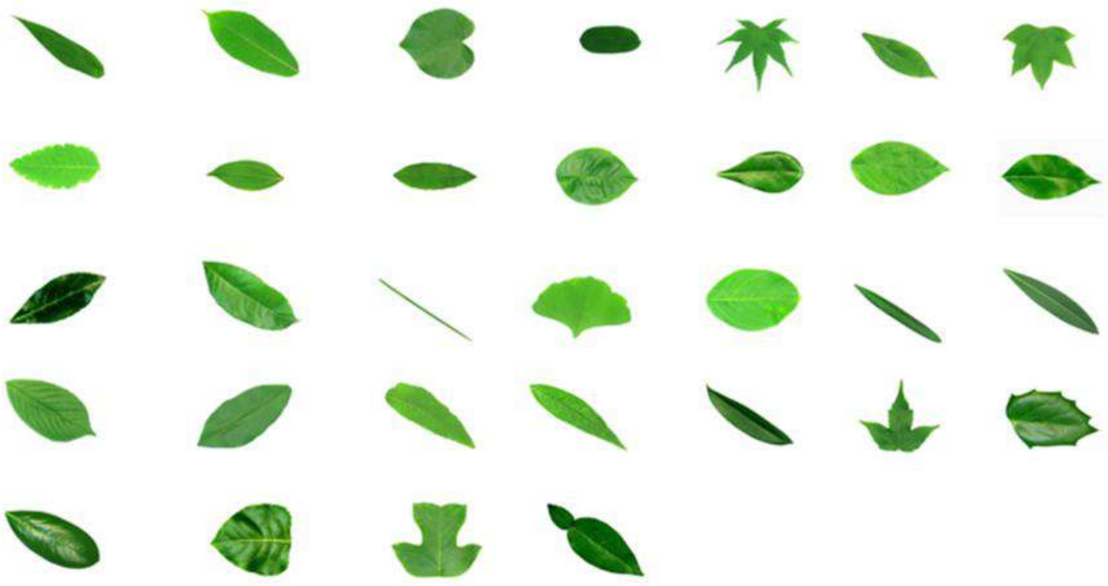

Figure 5.5 : Representative samples from Flavia dataset.

The evaluation of the used approach has been carried out on Flavia dataset [113]. Flavia contains 1907 images that are categorized into 32 classes. Figure 5.5 shows representative simples from this dataset. In our experiments, the dataset has been divided into two subsets. The First one consists of 1284 images (70%) used for training, whereas the rest 623 images (30%) have been used to test the system. We opted for Accuracy to be used as an evaluation metric of our system. It is given by the following formula (4).

$$\text{Accuracy (\%)} = \frac{\text{Nc}}{\text{Nt}} * 100 \qquad (4)$$

where Nc is the number of correctly classified images and Nt is the total number test.

In order to prove the performance of our method, we have firstly classify images using independently each classifier. Table 5.1 shows the obtained results.

Table 5.1 : Accuracy results using each classifier separately.

Classifier	**Average accuracy %**
NB	72,231
KNN	65,810
SVM	59,390

From Table 5.1 we can see that the best result has been yielded by naive-bayes (72%). Because it makes use of all the features contained in the data, and analyses them individually as though they are equally important and independent of each other. Additionally, we can see that SVM has not perform well compared to the others (59%). This low performance can be attributed to the low-dimensionality of the used data [129].

After evaluating each classifier separately, we will, next, evaluate the combinations of different classifiers. The obtained results are shown in Figure 5.6.

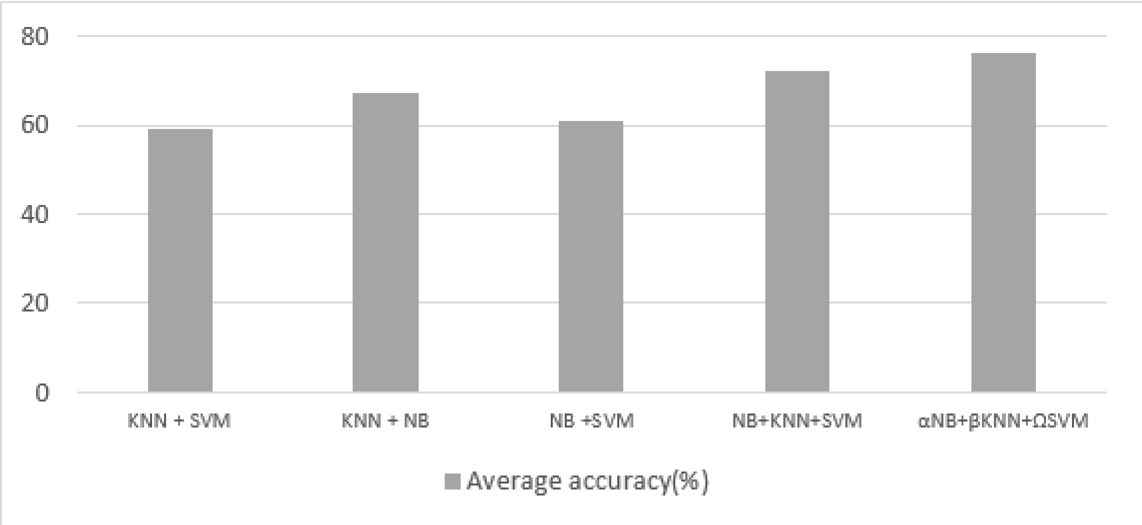

Figure 5.6 : Accuracy comparison of three clasiffiers.

As Figure 5.6 shows, combining classifiers does not improve results but rather decrease them in most cases. Because of suffering from low-dimensionality of data, SVM degrade the results of the different combinations by declaring conflicts in classification. Such issue could be resolved by assigning weights to the different classifiers. Thus and according to Table 5.1, the best classifiers has been associated with higher weights, combined then evaluated (i.e., $\alpha = 2, \beta = 2, \Omega = 1$). The values of weights have been chosen empirically based on training phase results. A classifier that has achieved a good result in this phase is assigned a high weight. As it is illustrated in Figure 5.6, combining these three classifiers with their corresponding weighs has yielded better results (76%).

5.4 Conclusion

In this paper, we have proposed an automatic plant classification system. Our system is based on a parallel combination of three classifiers namely KNN, NB and SVM with two combining modules namely sample majority vote and weighted vote. These classifiers are firstly trained with a set of morphological features that describes the shape of the leaf. Our system has been evaluated using the well-known Flavia dataset. After evaluating each classifier separately, we have found out that NB is the best classifier among all. We, then evaluate the different possible combinations of classifiers. Results indicates that SVM negatively effects the results because of the low-dimensionality of data especially by using simple majority vote module. To solve this issue, we have opted for weighted vote with the following weights 2, 2 and 1 that corresponds respectively to NB, KNN and SVM. By associating the lowest weight to SVM, our system reduces its negative effect to the voting process. The former combination has yielded best results. Future works should consider using more powerful classifiers such as neural networks or discriminate analysis.

Chapter 6

6 Automatic recognition of plant leaves using serial combination of classifiers

Contents

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Automatic recognition of plant leaves using serial combination of classifiers

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Abstract

Plants are of great importance in human life, they are useful in many field such as industry, medicine, agriculture, etc. Plant identification is not a trivial task and presents challenges even for specialists. In this paper, we present an automatic leaf classification system based on a serial combination of two classifiers, namely: Linear discriminate analysis and Naïve Bayes. Our system is consisted of two stages, at the first stage, NB classifier attempts to determine, with a reject option, the class that a given sample is belonging to. If the confidence score yielded by NB does not exceed a certain threshold, then the sample will be passed through another classification task using LDA classifier. Our system has been evaluated using the well-known Swedish dataset. Experimental results indicated that the serial combination of the classifiers has shown better performance than those obtained using only one classifier.

Keywords: plant leaves; morphological features; serial combination; classification.

6.1 Introduction

Computer vision is a rapidly growing field. Therefore, Image classification and recognition tasks gained a lot of interest due to the increasing computing capabilities of modern computers. Plant leaf classification became a hot research topic [121] in recent years. Many industry fields benefit from these researches such as medicine, economic agriculture, etc.

The classical plant classification depends mostly on manual recognition using molecular biology and cellular features of leaves. However, the huge number of species that exist in the world makes classification through experts and botanists subjective, slow, difficult, and sometimes not accurate [114]. Subsequently, an automatic plant identification system that facilitate and accelerate the process of identification is highly needed.

Plants are usually recognized using their leaves, stems, fruits or flowers. Leaves seem to be the most suitable parts that can be used to identify a plant. This is due to their availability in all seasons. In addition, leaves flatness makes it easy to be represented by the computer in 2D.

Because of the improvement achieved in machine learning, the automatic identification of plants has become possible. So far, researchers have done a lot of work concerning plant recognition using machine-learning approaches.

Pedro et al. [114] have presented an approach to identify medicinal plants such as herbs, shrubs and trees automatically. As a classifier, they have used Artificial Neural Network (ANN) and Support Vector Machine (SVM). Hariri et al. [91] presented a system based on Random Forest (RF) and Linear Discriminant Analysis (LDA) algorithms for identifying different types of plants using feature combination, the experimental results showed that LDA achieved a classification accuracy of 92.65 %. Wu et al. [113] introduced a system to classify 32 plant species by extracting 12 visual features from the leaf. KNN classifier has been trained with1800 leaf images and achieved an accuracy of 93 % (1-NN) and 92 % (4-NN).

In literature, most works have opted for only one classifier. Thus, some recent works have tried to improve the results by combining more than one classifier. In [122], authors present a system based on the serial combination of two SVMs. The idea was to devote one classifier for color features and the other one for both shape and texture features. Their evaluation has been carried out on a dataset that contains six plant diseases. The experimental results have reported an 87.7% accuracy.

In this paper, we introduce a system that combines two classifiers sequentially, namely LDA an NB. As features, we consider extracting shape and texture features (i.e. Morphological and LBP) from the leaf images. The evaluation of our system has been undergone the well-known Swedish dataset. More details about the proposed system will be given in the next section.

The rest of the paper is organized as follow: section 2 presents the scheme of our system and discusses the used features. In section 3, we conduct experimentations on the proposed system and report results. Finally, we give some conclusions.

6.2 Proposed Method

In this section, we explain our proposed method for leaf identification that consists of two main phases: feature extraction and classification. At the first phase we extract two type of features from the leaf image, the first type is texture features (LBP) and the second types shape features (Morphological). At the second phase, we train the first classifier with LBP and the second classifier with Morphological features. Finally, the tested images is passed on a serial combination of the two classifier in order to yield the global response. Figure 6.1 illustrates a general scheme of our system.

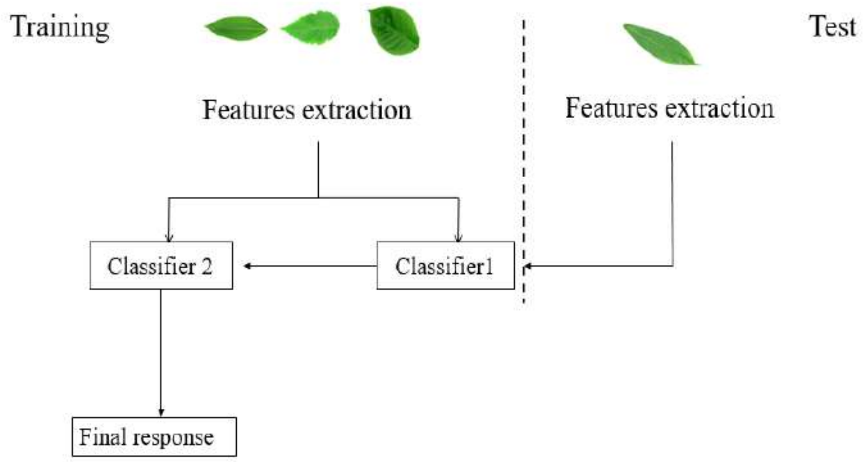

Figure 6.1: Scheme of the proposed system.

1. Feature extraction

The features extraction stage consists in transforming the segmented image into a vector of numeric values. The adopted features include LBP that is regarded as a powerful tool for extracting robust features from texture images, and Morphological features that describe the shape of leaf.

- **Morphological Features:**

In this stage and after having the original image transformed into binary, we extract a set of shape features that describe the morphology of a leaf. Morphological features are obtained by extracting the basic geometrical properties [1] of the leaf such as: diameter, area, perimeter, major and minor. Figure 6.2 shows an example of some geometrical features extracted from a leaf image.

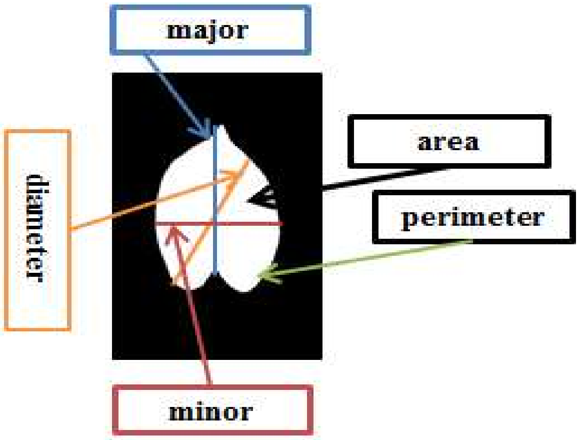

Figure 6.2: Basic geometrical features.

In our method, we extract the following five morphological features:

1. Diameter: is the longest distance between two points of the leaf contour D.
2. Area: is the number of pixels that constitute the area of the leaf.
3. Major axis length: is the distance between two terminal points orthogonal to minor axis length LP.
4. Minor axis length: is the longest distance orthogonal to major axis length WD.
5. Perimeter: the number of pixels at the margin of the leaf P.

In addition, and based on these features, we extract another set of digital morphological features that were introduced by the authors of [1] which are :

1. Aspect Ratio: is defined as the ratio of major axis length LP to minor axis length WP. It is also called Eccentricity or Slimness. It is given by Aspect Ratio=LP/WP.

1. Perimeter Ratio of Physiological length & width: this features is the ratio of perimeter leaf and the sum of major and minor axis length, given by PRPW=P/(LP+WP).
2. Perimeter Ratio of Diameter: it is the ratio of perimeter to the diameter, given by PRD=P/D.
3. Rectangularity: The similarity between the leaf and a rectangle, given by R=(Lp*Wp)/A.
4. Narrow Factor: the ratio of the diameter D and length Lp (i.e., NF = D/Lp).
5. Circularity: The ratio involving the area A of the leaf and the square of its perimeter P, given by $C = 4\pi A/p^2$.
6. Solidity: The ratio between A (area) of the leaf and Ach (area of a convex hull), given by S = A/Ach.

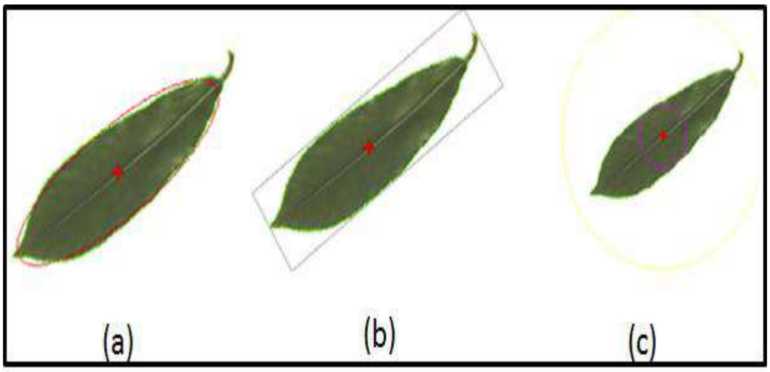

Figure 6.3 : (a) Elliptic form, (b) Rectangularity, (c) Circularity.

- **LBP (local binary pattern):**

Local Binary pattern (LBP) was firstly introduced by Ojala [48] and Pietkain as a statistical approach. A very small local neighborhood (patch) of a pixel is used to calculate a feature vector. The LBP operator labels the pixels of an image by thresholding the local neighborhood around each pixel and considering the result as a binary number. Figure 6.4 illustrates an example of computing LBP in a 3×3 neighborhood by comparing the intensities of the eight neighbors around each pixel with the intensity of the center pixel.

5	13	20
6	10	3
16	70	55

→

0	1	1
0		0
1	1	1

1	2	4
128		8
64	32	16

→

0	2	4
0		0
64	32	16

Figure 6.4 : LBP.

LBP=0*1+1*2+1*4+0*8+1*16+1*32+1*64=118

2. Classification

Image classification is the process in which images are recognized, differentiated, and understood. The classifier, firstly, is trained with a set of labeled data (i.e., training set). Then, test samples are provided to the classifier in order to be assigned to the appropriate class.

In our work, the feature vectors, which are extracted in the previous phase, will be used to train our system. It consists of two stages, in the first stage we adopt NB [134] classifier and in the second one we use LDA [90]. Serial approach [135] is used to combine the classifiers, which consists in positioning the classifiers one after the other. The successive organization of classifiers permit to either improve the decision taken at the previous stage or leave it as it is.

In our work, the recognition process may undergo one or two stages. If the first classifier has yielded a decision that exceeds a certain threshold, then no second classification stage is needed. Otherwise, if the decision is below a certain threshold, then the sample must be fed to the second classifier in order to improve the decision.

The utilized classifiers are presented below:

A. NB (Naïve Bayes):

Naive Bayes classifiers [136] are family of simple probabilistic classifiers that apply Bayes' theorem with strong (naive) independence assumptions between the features.

Let x be a data sample whose class label is unknown and let c be some hypothesis, then.

$$P(c/x) = \frac{P(x/c)P(c)}{P(x)} \quad (1)$$

The naive Bayes classifier requires a small amount of training data to estimate the necessary parameters (means and variances of the variables) for classification. Because independent variables are assumed, only the variances of the variables for each class are need to be determined and not the entire covariance matrix.

Naive Bayes conditional independence assumption, assume that probability of observing the conjunction of attributes is equal to the product of the individual probabilities $p(x_i/c_i)$.

$$C_{nb} = \operatorname{argmax} P(c_j) \prod_i p(x_i/c_j) \quad (2)$$

B. LDA (Linear Discriminant Analysis):

Linear Discriminant Analysis (LDA) is a commonly used technique for data classification and dimensionality reduction. Linear Discriminant Analysis easily handles the case where the within class frequencies are unequal and their performances have been examined on randomly generated test data. Its basic idea is to find a linear transformation that best discriminate the classes, and then classification can be performed in a transformed space based on some metrics such as Euclidean distance. [91]. Mathematically, LDA implementation is carried out via scatter matrix analysis. For all samples of all classes, two measures have been defined as follows:

Within-class scatter matrix is defined by the following formula:

$$S_w = \sum_{j=1}^{k} \sum_{i=1}^{N_j} (x_i^j - m_k)\,(x_i^j - m_k)^T \quad (3)$$

Between-class scatter matrix, which is defined by the following formula:

$$S_B = \sum_{j=1}^{k} (m_k - m)\,(m_k - m)^T \quad (4)$$

6.3 Experiment

In order to evaluate our system, we have used the well-known Swedish dataset [137] that contains 15 classes with a total of 1125 images. Figure. 6.5 shows a representative sample from this dataset.

Figure 6.5 : Representative sample of leaf.

In this experiment, the first 25 images from each class are devoted for the training and the rest 50 images are for the test.

We opted for Accuracy to be used as an evaluation metric of our system. It is given by the following formula.

$$\text{Accuracy } (\%) = \frac{\text{Nc}}{\text{Nt}} * 100$$

Where N_C is the number of correctly classified images and N_t is the total number of test images.

To prove the performance of our method, we firstly classify images using each classifier independently. Table 6.1 shows the obtained results.

Table 6.1 Accuracy results using each classifier separately.

Classifier	Features	Average accuracy%
NB	LBP	67.73
LDA	Morphological	65.38%

From Table 6.1 we can see that the results that have been yielded by NB and LDA are approximately the same. After evaluating each classifier separately, we evaluate the combination of the two classifiers using a threshold of 80%. The obtained results are shown in Table 6.2.

Table 6.2 Accuracy results using classifier combination.

Classifiers	Average accuracy%
LDA+NB	71.33

As Table 6.2 shows, combining classifiers sequentially has improved the results. This means that errors made by the first classifier have been corrected by the second one.

6.4 Conclusion

In this paper, we have proposed an automatic plant classification system. Our system is based on a sequential combination of two classifiers namely LDA and NB.

In order to create discrimination of the response between classifiers, the first classifier has been trained with a local binary pattern features and the second with Morphological features that describe the shape of the leaf. Our system has been evaluated using the well-known Swedish dataset. After evaluating each classifier separately, we have found out that LDA and NB has yielded approximately the same results. We have then evaluated a serial combination of classifiers where the result indicated better performance. Other types of classifiers should be sequentially combined and examined for leaf classification.

Chapter 7

7 A Comparative study of multiple parallel combination schemes for automatic plant leaf recognition

Contents

A Comparative Study Of multiple Parallel Combination Schemes For Automatic Plant leaf Recognition

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Abstract Plant identification is a crucial task in many fields including agriculture, pharmacy and environmental science. Considering the huge number of plant species and the high visual resemblance between certain of them, plant identification is a complicated task which requires a special knowledge. In this paper, we propose a comparaison of several parallel combination schemes for plant leaves classification based on shape and veins features. Particularly, leaves have been described using invariant morphological and vein features which are essential in distinguishing confusing species. For classification purposes, we consider using three classifiers namely support vector machine (SVM), Linear discriminate analysis (LDA) and naïve Bayes (NB). To further improve the classification outcomes, we investigate different parallel combination schemes including Naïve Bayes, majority vote and fixed schemes. The proposed method has been evaluated on two public datasets namely Flavia and Swedish. Experimental results have depicts that combination methods prove its supermency compared to certain state of the art methods and NB methods has recorded the best results.

Keywords: classifier combination, leaves classification, morphological features, plants identification.

7.1 Introduction

Plants have a significant impact on human's life and development, without them there will be no existence of the earth's ecology [138]. Plants play a decisive role in providing clean air, food, medicine and oxygen. Besides, they contribute in facilitating the task of scientists from the different domains such as agriculture, medicine and environmental fields. The earth hosts a huge number of plant species with range between 220,000 [139, 140] and 420,000 [141]species, some of them are subject to the danger of extinction [27]. Thus, establishing a plant database, which catalogues the plant diversities, is a quite important step towards protecting plants from this danger. Traditionally, botanists classify plants manually by using molecular biology and cellular features of leaves. Nevertheless, classification through experts and botanists is subjective requires much effort from experts and it is too expensive in terms of time. On the contrary, automatically performing such a task, using machine learning techniques, is rapid, inexpensive and accurate as well.

Automatic plant identification (i.e., classification) has become a hot research topic in recent years [8]. Plants can be classified using their organs such leaves, stems, fruits or flowers [67]. Nevertheless, leaf is the most adopted part for the recognition purposes because it carries out plant's inherent properties and it is available all the seasons, contrary to the other parts. In addition, the leaf flatness makes easy to represent it by computer. Leaves can be characterized based on their shape [124, 142, 143], texture [125, 144, 145], veins [113], and color [85]. Leaf color may vary over time and under different environmental conditions. In addition, leaves from different plant species may share a common color (e.g., green) thus, color solely cannot be used to discriminate plant species, and it has been ignored by many works [58].

In literature, many researchers have attempted to put forward systems that are capable of automatically identifying plant species based on leaf images some approaches [146] have resorted to feature combinations techniques in order to improve the recognition rate, whereas some others have tackled the problem by introducing special discriminative plant leaf features [124]. Despite the considerable efforts that have been done by researchers, plant identification from leaf images is still an open issue because of the huge number of plant species. Recently, several studies have tried to propose new systems that employ multiple classifiers simultaneously rather than one single classifiers. Researchers arrived at such an approach by the intuition telling that a decision taken by multiple classifiers should be better than the one taken by one single classifier.

Multiple classifier system approaches have been successfully applied in solving different issues including facial expression recognition [146], medicine classification [147] and others. The MCS approaches can roughly be categorized into parallel, sequential and hybrid [148]. Parallel approach is often adopted to improve classification accuracy, whereas sequential approach is mainly used for accelerating the classification in the case of large-scale datasets (i.e., high number of categories). the combination of the two approaches mentioned above is considered as hybrid approach.

In this paper, we put forward a method for automatic plant leaves recognition based on a multiple classifiers combination in the aim of comparaison. In particular, we describe the leaves using different features, including morphological features, which are invariant to translation, scale and rotation. As instance, we extract vein features, which could be useful in distinguishing the different species. Indeed, we opt for using such features because of their capabilities in describing the leaf from different aspects. To perform classification, we have considered three classifiers namely support vector machine (SVM), Linear discriminate analysis (LDA) and naïve Bayes (NB). To further improve the classification results, we propose to use different classifier combination schemes. Especially, we investigate the strength of Naïve Bayes scheme, majority vote and fixed schemes such as sum and product of classifiers responses. The evaluation of the proposed method is carried out on two well-known datasets namely Flavia and Swedish. Experimental results have demonstrated the efficiency of our method and a noteworthy performance has been reached compared to certain other methods.

The remainder of this paper is organized as follows. A brief review of related work is presented in Section 2. In Section 3, we describe the details of the proposed method. Experimental results are provided in Section 4. The final section presents our conclusions and future work.

7.2 Related work

In recent years, a lot of efforts have been made to achieve more reliability in automatic leaf recognition. In general, the recognition system consists in two stages namely: feature extraction, and image classification stage. According to [24] [25] leaf features are categorized into two categories which are: general visual features and domain related visual features. General visual features, such as color, texture and shape features, were not designed for leaf images only, but rather for all types of images regardless the content. Whereas, domain-related visual features, are specified for leaf images, those features are based on the morphology of the leaf, such as shape, dent and vein.

Recently, Hu et al. [32] proposed a contour-based shape descriptor named multiscale distance matrix (MDM) for fast plant leaf recognition. They used the matrix of pairwise distances between points sampled on the boundary of a leaf to capture the geometric structure of the shape. MDM is invariant to translation, rotation, scaling, and bilateral symmetry. MDM is considered as a very effective method since it avoids the use of dynamic programming for building the point-wise correspondence, compared to other contour- based approaches. Ling et al. [29] proposed the well-known shape description method (IDSC) which used inner-distance instead of Euclidean distance to build the shape context, to achieve robustness against articulation. They achieved recognition rate of 94.13% in Swedish dataset. In [34] Wang et al. proposed a method that uses a multi-scale arch height (MARCH) features at different chord spans extracted from each contour point. This algorithm aims to effectively capture the global and detailed characteristics and provides a coarse-to-fine shape description of the leaf. The recognition rate was calculated using the 1-Nearest-Neighbor classifier, and a prototype system for online plant leaf identification was developed for use on a mobile platform. Whilst leaf shape may be sufficient to distinguish between some species, shapes of some other species may be highly similar which prevents their identification. Such a problem could be remedy by exploiting color and texture features of the leaf. Typically, Ghasab et al. in [149] use as texture features derived from GLCM, namely contrast, correlation, energy, homogeneity, and entropy and combine them with shape, color, and vein features. The system was tested on around 2050 leaf images collected from two different plant databases. In [150] Bhardwaj et al. used moment invariant and texture as features for plant identification. This method obtained an accuracy of 91.5% when performed on a database containing 320 leaves of 14 plant species. Recently, Tsolakidis et al. [151] used Zernike moments and histogram of oriented gradients as features for leaf image, for which they obtained an accuracy of 97.18% on the Flavia database. in [118], Kadir et al. to build foliage plant identification systems. Zernike moments were combined with other features: geometric features, color moments and gray-level co-occurrence matrix (GLCM). The geometric features include aspect ratio, circularity, irregularity, solidity, convexity and two types of vein features are used and color, the results show that Zernike Moments have a prospect as features in leaf identification systems when they are combined with other features. Du et al [152] proposed another leaf classification system based on geometrical features. They have identified 8 geometrical features in addition to 7 moment invariants. Their proposed system performs linear scaling and Wilson Editing method which uses Moving Center Hypersphere Classifier (MCHC). MCHC was proposed specifically for leaf classification.

As we said above, leaf recognition relies on feature extraction and image classification. Regarding this second aspect, numerous classifiers have been used in the literature. In [152] Wu et al. a Probabilistic Neural Network (PNN) is used to classify leaves. In this method, PCA is used to orthogonalize the 12 morphological parameters derived from 5 basic geometrical features (e.g., diameter, physiological length, physiological width, leaf area and perimeter) extracted from the segmented binary leaf images. The method requires manual entry of the start and end points of the midrib, and hence is not fully automatic. El Hariri et al. [91] presented a classification approach based on random forest (RF) and Linear Discriminant Analysis (LDA) for classifying the different types of plants. The experimental results showed that LDA achieved classification accuracy of 92.65 % with combination of shape, texture, and vein features. Prasad et al. [153] proposed an SVM-based system for plant leaf identification and classification, 300 leaf features were extracted from a single leaf of 624 leaf dataset to classify 23 different kinds of plant species. Harish et al. [1] have opted for SVM classifier to automatically identify leaf images based on the extracted morphological features and Zernike moments. the classification with SVM gives a good accuracy in all most times [154], but it is a binary classifier, the training is slow, in addition to the difficulties of understanding the structure of the algorithm. In [155], Shilpa et al. proposed a system in which Fuzzy C-Means is used for clustering images and Naïve Bayesian classification to classify the leaf image. They resort to a leaf extraction method from a given image by using some shape-based features. The proposed method yields an accuracy of 83.24%. A weakness of Bayesian classifiers is that conditional independence may decrease a constraint over attributes that may not be dependent [156]. Zhang et al. [152] present a method of plant leaf classification based on KNN as classifier and histogram of oriented gradients (HOG) as feature. KNN is a simple technique, but it is computationally expensive to find the K nearest neighbors when the dataset is very large and. In addition, the accuracy can considerably tumble down in the presence of noisy or irrelevant features.

No single feature may be sufficient to separate all the categories, making feature selection and description is a challenging problem. Typically, this is the innovative part of the studies we reviewed. Indeed, feature combinations improve performance. However, a classifier that shows a high performance in one datasets, may not show the same performance in another dataset. This issues lead researcher in recent years to study the effect of combining multiple classifiers at a decision level. Such an approach has shown promising results [14,15,[157].In [122] as instance, El Massi et al. suggest using a serial combination of two SVMs. Their main idea was to devote the first SVM classifier to classify images using color features, and the second SVM using shape and texture features. Their evaluation has been carried out on a dataset that contains six disease classes. The system reports an 87.7% accuracy. In [123] Essaady et al. have used a parallel combination of two classifiers: ANN was devoted to classify images using texture, color and shape as features, whereas SVM was devoted to classify images using shape and texture features The evaluation has been carried out on a dataset of six disease classes and they reported 91.46% accuracy.

Despite the improvement brought by multiple classifier system in several domains, in literature few researchers in the field of leaf recognition consider this technique. In this paper we have investigated and compared results of several parallel combination methods MCS (Multiple Classifier System).

7.3 Proposed Method

The proposed method consists in two stages namely features extraction and classification. In the first stage, several morphological features, including circularity, rectangularity, form factor, aspect ratio, were extracted. In the second stage, we had to use multiple classifiers. Using multiple classifiers should meet an essential criterion which is the high diversity between them [158]. A high diversity simply means that when a classifier makes a wrong decision, the others weren't make the same decision. According to our experiments, SVM, LDA and NB classifiers found to have the highest diversity among others. All classifiers are trained using the same features that we extracted from the leaves, we have investigated different classifier combination schemes. In particular, we propose to use parallel combination schemes including: Fixed rules, Majority vote, and Naïve Bayes method.Figure. 7.1, illustrates the general scheme of the proposed method. Hereafter, we provide the details of the proposed method.

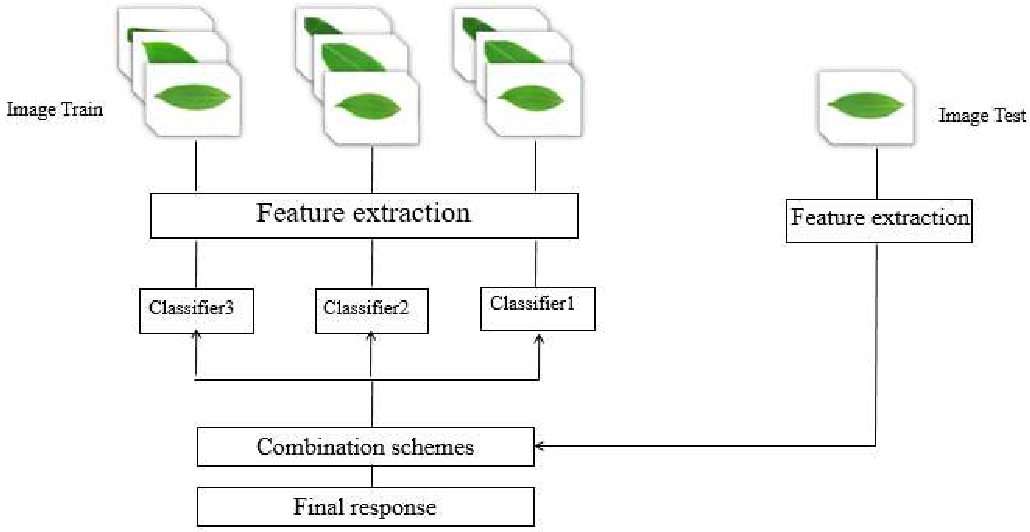


Figure 7.1: General scheme of the proposed system.

1. Feature extraction

Several morphological features have been extracted. They are very important as they provide critical information about leaf morphology, which could facilitate the process of distinguishing different leaves species. Morphological features are obtained by extracting the basic geometrical properties [10] of the leaf such as: diameter, area, perimeter, major and minor. Figure 7.2 shows an example of basic geometrical features extracted from a leaf image.

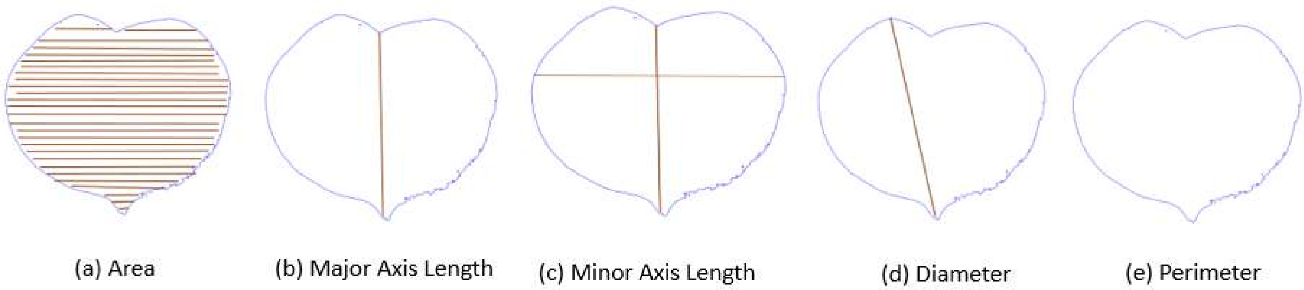


Figure 7.2 : basic geometrical features.

In our method, we extract the following basic geometrical features

1) *Diameter:* is defined as the longest distance between any two points on the margin of the leaf. It is denoted as D.
2) *Area:* is the number of pixels that constitute the area of the leaf. It is denoted as A.
3) *Major axis length*: is the distance between two terminal points of main vein of the leaf, it is orthogonal to minor axis length. It is denoted asl_p
4) *Minor axis length:* is the longest width distance that is perpendicular to the major axis length It is denoted as w_D.
5) *Perimeter:* leaf perimeter is calculated by counting the number of pixels forming the leaf margin. It is denoted as P.

Based on the above features, ten morphological features have been used [11] [29], which are:

Aspect Ratio: it is defined as the ratio of major axis length $l_p$to minor axis length w_P. It is also called Eccentricity or Slimness. It is given by as *:* l_p/w_P (1)

Perimeter Ratio of Physiological length & width: is the ratio of perimeter leaf and the sum of major and minor axis length, it defined as $P/(l_p + w_P)$ (2)

Perimeter Ratio of Diameter: it is the ratio of perimeter to the diameter, it is calculate as P/D (3).

Rectangularity: measures how rectangular the leaf is, it is given by $(\mathrm{l_p} * \mathrm{w_P})/\mathrm{P}$ (4)

Narrow Factor: the ratio of the diameter Dand length $\mathrm{l_p}$is computed as $\mathrm{D/l_p}$ (5).

Circularity: this measures how circular the leaf is , it is given by $4\pi\mathrm{A/p^2}$ (6).

Solidity: the ratio between A area of the leaf and $\boldsymbol{Ach}$ the area of a convex hull it is computed as A/Ach (7).

Vein features: in order to obtain veins, we perform morphological opening [28] on grayscale image with flat, disk-shaped structuring element of radius 1,2,3,4 and subtract remained image by the margin. The results look like the vein. That is why following 5 feature are called vein features. Areas of left pixels are denoted as Av1, Av2, Av3 and Av4 respectively. Then, we obtain the last 5 features: Av1/A, Av2/A, Av3/A, Av4/A, Av4/Av1 (8)**.**

Smooth factor: The effect of noise to image area is used to illustrate the smoothness of leaf image. Smooth factor is given as the ratio between area of leaf image smoothed by 5 × 5 rectangular averaging filter and the one smoothed by 2 × 2 rectangular averaging filter. Figure 7.3 presents some morphological features.

Figure 7.3: Morphological features. (a). solidity, (b). Aspect Ratio, (c). Rectangularity (d). Circularity.

And in order to benefit from basic morphological which they contributed to distinguished between species we have considered (area, major axis length, minor axis length, filled area) as additional features.

2. Classification

Classification is the process in which images are recognized, differentiated, and understood. The classifier is firstly trained using a set of labeled data to produce a mapping function which is further used to classify new data samples. Parallel combination of classifiers has become a hot area of research in the recent years, it is successfully applied in many applications such as handwriting recognition [159], facial expression [146] and digit identification [160].

In our work, we have opted for three classifiers namely NB [161], SVM [128],16] and LDA [162] which hold the highest diversity. In order to obtain the final response, we have combined them in parallel combination approach. unlike to the other two approaches, parallel approach it does not need to know precisely the behavior and the order of classifier [163]. Parallel approaches are thus more easily generalizable and easier to implement since they simply require the development of a combination stage of the outputs.

A. Classifier

the classifier considered in our method is Naïve Bayes, Support vector Machine and linear discriminant analysis the theoretical background of them is presented in the following.

1. Naive Bayes (NB)

Naive Bayes is an effective probabilistic classification algorithm [161], which is based on applying Bayes' theorem. It assumes the attribute variables to be independent from each other. A classification issue can be seen as the problem of finding the outcome with maximum probability given a set of observed variables.

Given x_i where i ={1,2, ... , n} is a feature vector and c_j is class j where j={1,2, ... , m}

The probability that x_i belongs to c_j is calculated as in Eq (9)

$$P(c_j/x_i) = \frac{\mathrm{P}(x_i/c_j)\mathrm{P}(c_j)}{\mathrm{P}(x_i)} \quad (10)$$

where:

$P(c_j/x_i)$: probability of instance x being in class c_j (i.e., target) given instance x (i.e., attributes).

$\mathrm{P}(c_j)$: is the prior probability of the class c_j

$\mathrm{P}(x_i/c_j)$: is the likelihood, which is the probability of instance x given a class j.

$\mathrm{P}(x_i)$: is the prior probability of instance.

x_i is classified to the class having obtained the maximum probability.

Naive Bayes conditional independence assumption, assume that probability of observing the conjunction of attributes is equal to the product of the individual probabilities $p(x_i/c_i)$.

$$\mathrm{C_{nb}} = \mathrm{argmaxP}(\mathrm{c_j}) \prod_{\mathrm{i}} \mathrm{p}(\mathrm{x_i}/\mathrm{c_j}) \qquad (11)$$

2. Support Vector Machine (SVM)

SVM [74] is a supervised classifier which enables finding the optimal separating hyper plan maximizing the margin between the two classes, the decision surface is a weighted combination of training set elements. Those elements characterize the boundary between two classes and are called support vectors. The input to a SVM algorithm is a set $s = \{(x_i, y_i)\}$ of labeled training data, where x_i is the data and , y_i = -1 or 1 is the label. The output of SVM is a set of N_s support vectors s_i, coefficient weights a_i , class labels , y_i of the support vectors, and a constant term b. The linear decision surface is represented as:

$$w.z + b = 0 \qquad (12)$$

$w = \sum_{i}^{Ns} a_i \ y_i s_i$ (13)

In the case where features are not linearly separable, a kernel function is used to map the input space to a higher dimensional space, in which features are linearly separable. (i,e Gaussian kernel), which is given by the flowing equation:

$$k(X_{i,}X_j) = \exp(-\frac{\|x_{i,} - x_j\|^2}{2\sigma^2}) \quad (14)$$

3. Linear Discriminant Analysis (LDA) multi class

Fisher's linear discriminant analysis (LDA) [162] is a classical classifier and a dimension reduction method too. Its basic idea is to find a linear transformation that best discriminates among classes, then classification can be performed in transformed space based on some metrics such as Euclidean distance. Let D = $\{(x_i, y_i)\}$be a labeled dataset with I = $1, \dots, k$ output examples. Every d-dimensional vector $x_i$is associated to one of K possible class labels $y_i \in \{1, \dots, k\}$. Let $m_k \in R^d$ be the centroid of class k (with k =$1, \dots, k$), $p_k \in$ R be the estimated proportion of class k in the whole dataset, $\sum_w$ be the pooled within-class covariance matrix of the inputs and $\bar{m} = \sum_k p_k m_k$ be the dataset mean. LDA finds β $\in R^d$ such that $\beta^T \sum_K \beta = \beta^T \sum_{i=1}^{K} p_k (m_k - \bar{m})\ (m_k - \bar{m})^T\ \beta$ (1) is maximized subject to the constraint $\beta^T \sum_K \beta$ =1, where $\sum_B$ =$\sum_K p_k (m_k - \bar{m})\ (m_k - \bar{m})^T$denotes the inter-class covariance matrix. Each β vector is a scaled Eigenvector $\sum_w^1 \sum_B$of representing each one of the directions in which the class means are most separable in the transformed space relative to the within-class covariance.

B. Combination methods

Each classifier in our system is trained with the same data, then the responses of each single classifier are fused using different combination methods to obtain the final decision i.e., response. Let x ∈ R^d be a feature vector $d = \{1,2, \dots, k\}$ and $\{1,2, \dots, m\}$be the label set of m classes where $C = \{c_j, j = 1 \dots m\}$, and D_s= $\{s = 1,2, \dots, L\}$a set of classifiers. Each classifier takes as an input a feature vector x ∈ R^d. The classifier output is a T -dimensional vector$[d_{i,1}(x), \dots, d_{i,j}(x)]$, where $d_{i,j}(x)$is the degree of ‘‘support’’ given by classifier D_s to the hypothesis that $x_i$where i=$\{1,2, \dots, n\}$comes from class j / j=$\{1,2, \dots, m\}$.

The output of classifiers decision is classified as: abstract level, rank level and measurement level.

- Abstract/class level: This is the most general utilized type, but brings the less information. The classifier in this case only gives the proposed type (class) of the entry to recognize without any other information$d_{i,j}(x) = \{0,1\}$.
- Rank level: this type of output reflects the order of preference of proposals provided by the classifier, this is translated by assigning a rank for each class. The class which is the more likely assigned, is assigned with the first rank, while the class positioned at the end of the list is the most unlikely. The list of proposals may contain the rank of all the possible classes or only the best ranked ones. $d_{i,j}(x) = [r_1^s, \dots, r_c^s]$ where $r_j^s$is the rank assigned to class (j)by classifier (s) for the data x_i.
- Measurement level: this output is the richest in terms of information since the

classifier in this case associates with each class a measure of confidence that can be, for example, a probability$[M_1^s, \dots, M_c^s]$ .where $M_j^s$is the measure assigned to class (j)by the classifier (s) for the data x_i.

There exist several combination methods. Fixed and trained. In [163] NB has proven its superiority. In our work, we have compared and evaluated NB and other Fixed methods. The combination schemes that we have adopted are: Naïve Bayes method, Majority Voting method and fixed methods including max, min, product, average and Sum. Hereafter, we present the methods in details.

Naive Bayes (NB):

Naïve Bayes combination (NB) scheme assumes that the classifiers are mutually independent this is the reason of the name naïve Bayes; Xu et al. [163] and others call it Bayes combination. For each classifier D_s a $c * c$ confusion matrix denoted as CM^s is calculated by applying D_s on the training data set. The $(k, u)^{th}$ entry of this matrix denoted as $cm_{k,u}^s$ is the number of elements of the data set whose true class label was k, and were assigned by D_s to class C. $cm_{.,u}^s$ Denotes the total number of elements labeled by D_s into class C . Using these values, a $c * c$ label matrix LM^s is computed, whose (k, u)th entry $lm_{k,u}^s$ is an estimate of the probability that the true label is k given that D_s assigns crisp class label u. $lm_{k,u}^s = \widehat{P}(k/\,D_s(x) = u) = cm_{k,u}^s / cm_{.,u}^s$.For every $x\,R^d$, D_s yields a crisp label vector $D_s(x)$ pointing at one of the classes lets say in $\{1,2, \dots, c\}$ associated with u is a soft label vector $\left[\widehat{P}(1/\,D_s(x) = u), \dots, \widehat{P}(c/\,D_s(x) = u)\right]^T$, which is the u th column of the label matrix LM^s. Let $[u_1, \dots, u_L]$ be the abstract class labels assigned to x by classifiers $D_1(x), \dots, D_L(x)$, respectively. Then, by the independence assumption, the estimate of the probability that the true class label is t (which is the t th component of the final label vector) is calculated by

$$q_{\widehat{D}}^t = \prod_{s=1}^{L} \widehat{P}(k/\,D_s(x) = u) = \prod_{s=1}^{L} lm_{k,u}^s\,, \quad t = 1, \dots, c \qquad (15)$$

Majority Vote:

This method consists in choosing the most class proposed by the classifiers.

$$E(x) = \begin{cases} c_j \text{if} \sum_{j=1}^{c} e_{i,j} = \max_{s=1}^{L} \sum_{j=1}^{c} e_{s,j} & (16) \\ \text{else reject} & \end{cases}$$

The output of each classifier(s)is considered to be a vote for a class jc_j of the data x_i. The number of votes for each class is counted, the selected class is the one having obtained the highest number of votes compared to the other classes. Nevertheless, there is a rejection if the classes obtain the same number of votes.

Fixed Method:

The basic principle behind these methods is that classifiers are independent and estimate posterior probabilities of classes measurement level is used in this methods. For a given data point x, a decision rule $E(x)$ is used, $E(x)$determines the class $C_j$for which the posterior probability p_j is the highest

$$E(x) = \begin{cases} c_j & \text{if } \max_{m=1}^{c} p_m \\ & \text{else reject} \end{cases} \quad (17)$$

The posterior probabilityp_m can be calculated according to one of the following rules

• **Product:** it combines the classifiers by multiplying the posterior probabilities, yielded by each classifierL for each class j. The product rule is shown by Eq (18)

$$\mathbf{p_m} = \prod_{s=1}^{L} d_{j,s}(x) \quad (18).$$

• **Maximum:** in this rule, the maximum posterior probability is considered for each class j given by each classifiersL, the max rule is given by the Eq (19)

$$\mathbf{p_m} = \max_{s=1}^{L} d_{j,s}(x) \quad (20).$$

• **Minimum:** in this rule, the minimum posterior probability is considered for each class j given by each classifiersL, the min rule is given by the Eq. (21)

$$\mathbf{p_m} = \min_{s=1}^{L} d_{j,s}(x) \quad (21).$$

• **Average:** the posterior probabilities yielded by the different classifiers are averaged, for each class jas shown by Eq. (22)

$$p_m = \text{median}_{s=1}^{L} d_{j,s}(x) \quad (22).$$

• **Sum:** this rule sum the posterior probabilities outputted by the different classifiers for each class j are obtained using the Eq (23)

$$p_m = \text{sum}_{s=1}^{L} d_{j,s}(x) \quad (23).$$

7.4 Experiment

This section is devoted to evaluate our proposed approach under different conditions (i.e., datasets and combination methods). In addition, we conduct a comparative evaluation against the combination methods between them and compared to other recent works in order to prove the effectiveness of the approach.

1. Datasets

Two widely known leaf datasets, namely Flavia [113] and Swedish [137], have been used in our experiments.

Flavia: Flavia [113] is a public leaf dataset that can be freely downloaded from the web [125]. It comprises 1907 leaf images categorized into 32 different species with the number of samples in each ranging from 50 to 77. Figure 7.4 shows representative samples from Flavia.

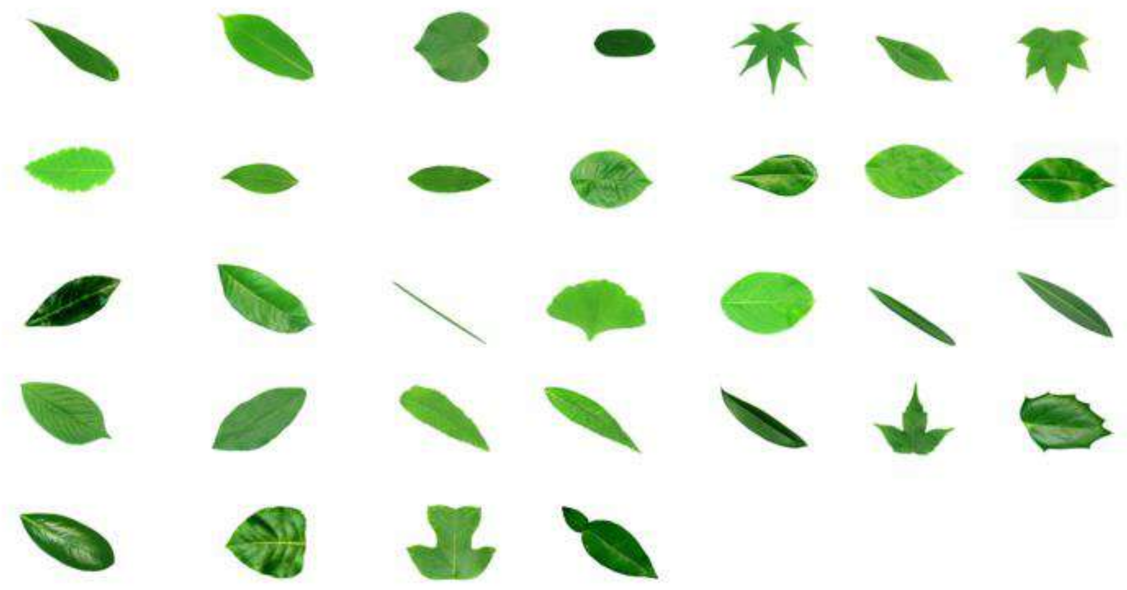


Figure 7.4 : Representative samples from Flavia dataset.

Swedish: The well-known Swedish dataset contains leaf images collected from Swedish trees. It consists of 15 species with 75 samples per each. This dataset is a publicly available on the web [137]. Figure 7.5 shows representative samples from Swedish dataset.

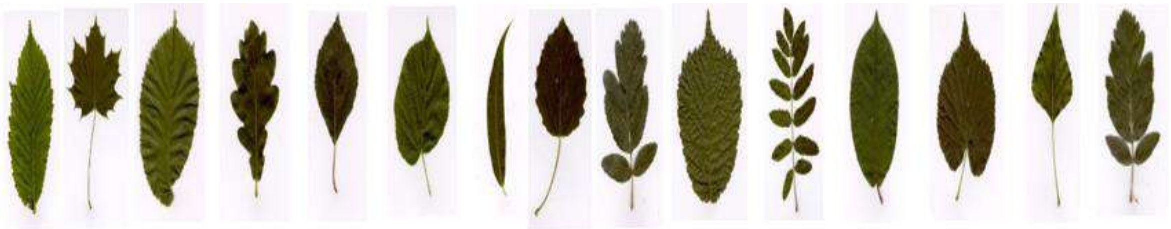


Figure 7.5: Representative samples from Swedish dataset.

2. Settings

Two separated experiments have been conducted using the above two real-word leaf image datasets. The first experiments consist of a comparison between the proposed method and some of the single-classifier-based methods. Additionally, a comparison among different classifier combination methods have been evaluated in order to determine which one holds the best performance. The second experiment aims at comparing the proposed method against other related works such as [113], [32], [34].

In order to evaluate our method, we have resorted to accuracy for the global performance measurement and confusion matrix for more detailed analysis.

$$Accuracy(\%) = \frac{Number\ of\ correctly\ classified\ test\ images}{Number\ of\ total\ test\ images} \times 100$$

- Results

The results obtained by using the two datasets (Flavia and Swedish) in the two experiments will be detailed in the following sections.

Experiment 1

In this experiment, the proposed approach, based on parallel combination of multiple classifiers, is compared with those using only one classifier. We have conducted 4 rounds of experiments that corresponds to the 4-folds. In each round for each fold, 75% of the images are dedicated to training, whereas the remaining 25% is for testing. The average accuracy and the standard deviation from the 4 experimental rounds are calculated. All the used classifiers are probabilistic, which means that the classification confidence is given by a probability $p \in [0\,,1]$. Table 7.1, quantitatively, presents the average accuracies obtained from the 4 evaluation rounds using single classifier-based approaches and combination-based approaches.

Table 7.1 : Average accuracies obtained by single-classifier-based approaches and our approach using different techniques of classifier combination.

Single-classifier based Methods	**Classifier**	**Flavia**	**Swedish**
	SVM	94.44% ± 0.41%	99.4% ± 0.67%
	NB	97.48% ± 0.48%	97.20% ± 0.71%
	LDA	90.66% ± 0.49%	73.95% ± 0.95%
Our method (SVM+LDA+NB)	Combination technique	Flavia	Swedish
	Majority vote	96.53% ± 0.37%	99.8% ± 0.69%
	NB	98.16% ± 0.35%	99.8% ± 0.69%

	MIN	98.06% ± 0.34%	99.00% ± 0.72%
	MAX	97.43% ± 0.34%	99.40% ± 0.71%
	AV	97.64% ± 0.34%	99.60% ± 0.70%
	PRO	98.11% ± 0.34%	99.00% ± 0.72%
	SUM	97.64% ± 0.34%	99.60% ± 0.70%

It is worth mentioning that there is a strong dependence between the classifier performance and the data or the problem it deals with [158]. Hence, we can observe that NB has outperformed the other classifiers on the Flavia dataset, whereas, SVM has yielded the best result on the Swedish dataset which comprises 15 species. In addition, the three single classifiers have yielded an average error-rate varying between 18-3% on both datasets which may not be considered as trivial especially in the medicine field. For this reason, combining the three classifiers could highly produce better results and alleviate the problem of choosing the classifier that best fits the data. As we can see, our adopted approach, that combines the three classifiers, has outperformed the methods based on one single classifier. Moreover, we can see that different results have been yielded for the different combination techniques. This means that the accuracy of the recognition system is not affected by the type of the combined classifiers only, but also by the technique used to combine them. In our experiments, the NB combination technique has yielded the best results. This could be attributed to its parametric priorities that utilize big base validation. We can see that the error rate has dropped to 0.94% in Flavia, and to 1.61% in Swedish, which leads to a significant improvement. The variation in results yielded by the other combination techniques could be explained by:

- The Majority Vote method technique is highly correlated to the Naïve Bayes technique. They, therefore, yielded similar performance.
- The Sum method is more resistant to classifier's errors than fixed rules, which leads to a competitive result.
- Min method has performed the worst because of its sensitivity to the erroneous decision produced by any classifier of the combination.
- Max and Product have obtained approximately the same result. These two techniques are also effected by the misclassification yielded by one classifier of the combination. In other words, if one classifier misclassified the sample x with a probability $p \approx 0$, then the global probability converges to 0 and accordingly to the erroneous decision. The same for Max when $p \approx 1$.

To have a clear idea about the performance gained by combining the three classifiers, we plot the Receiver Operator Characteristic (ROC) curve. To have ROC extracted, we firstly have to calculate the True Positive Rate (TPR) and False Positive Rate (FPR) for the 4 folds of the experiments. These two metrics are dedicated for evaluating binary classification decisions (positive/negative). Therefore, we transform our data into binary by, considering each time, one species as positive and the rest as negative. The TPR and FPR are calculated by:

$$TPR(\%) = \frac{Numberof\ positive\ testing\ images\ calssefied\ as\ Positive}{Numberof\ Poistive\ testing\ images} \times 100$$

$$FPR(\%) = \frac{Number\ of\ negative\ testing\ images\ calssefied\ as\ Positive}{Number\ of\ Poistive\ testing\ images} \times 100$$

Figure 7.6 and Table 7.2 presents the ROC, TPR and FPR obtained from single-based classifier methods and Naïve-based multiple classifier combination method. Area under the Curve (AUC) has been also calculated and presented.

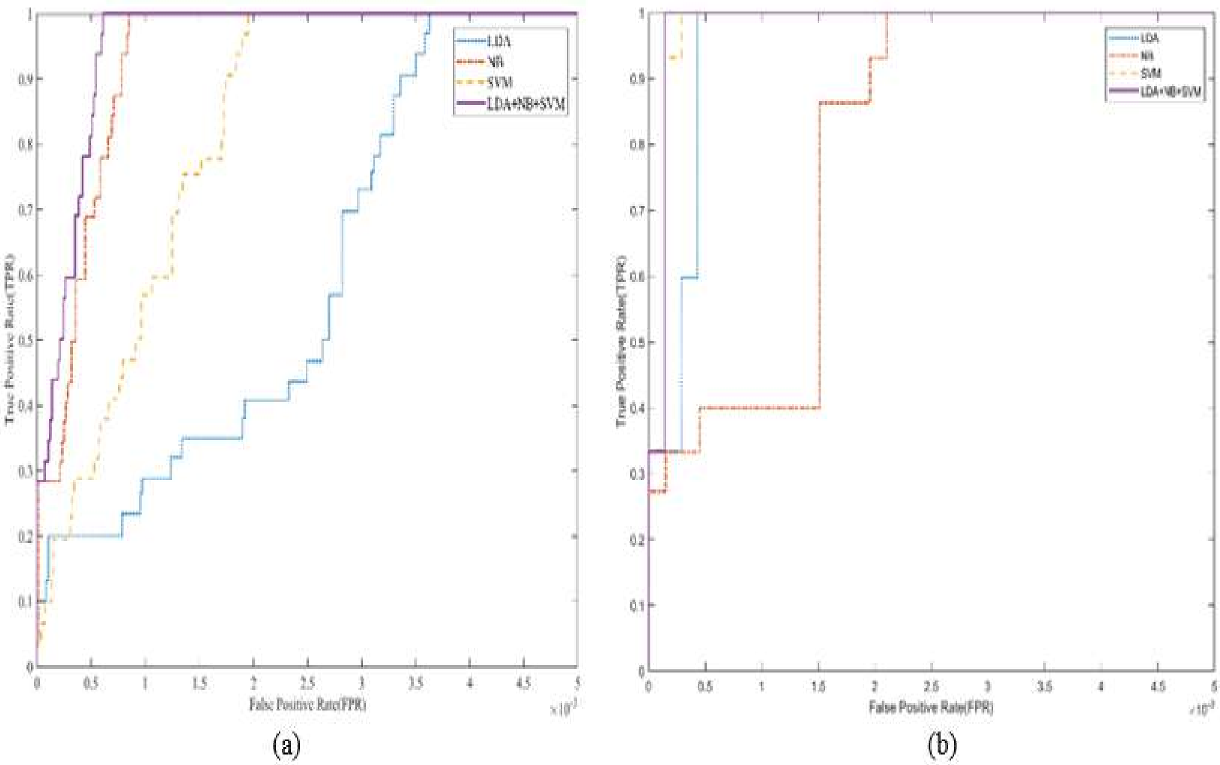


Figure 7.6: ROC curve obtained from (a) Flavia and (b) Swedish dataset.

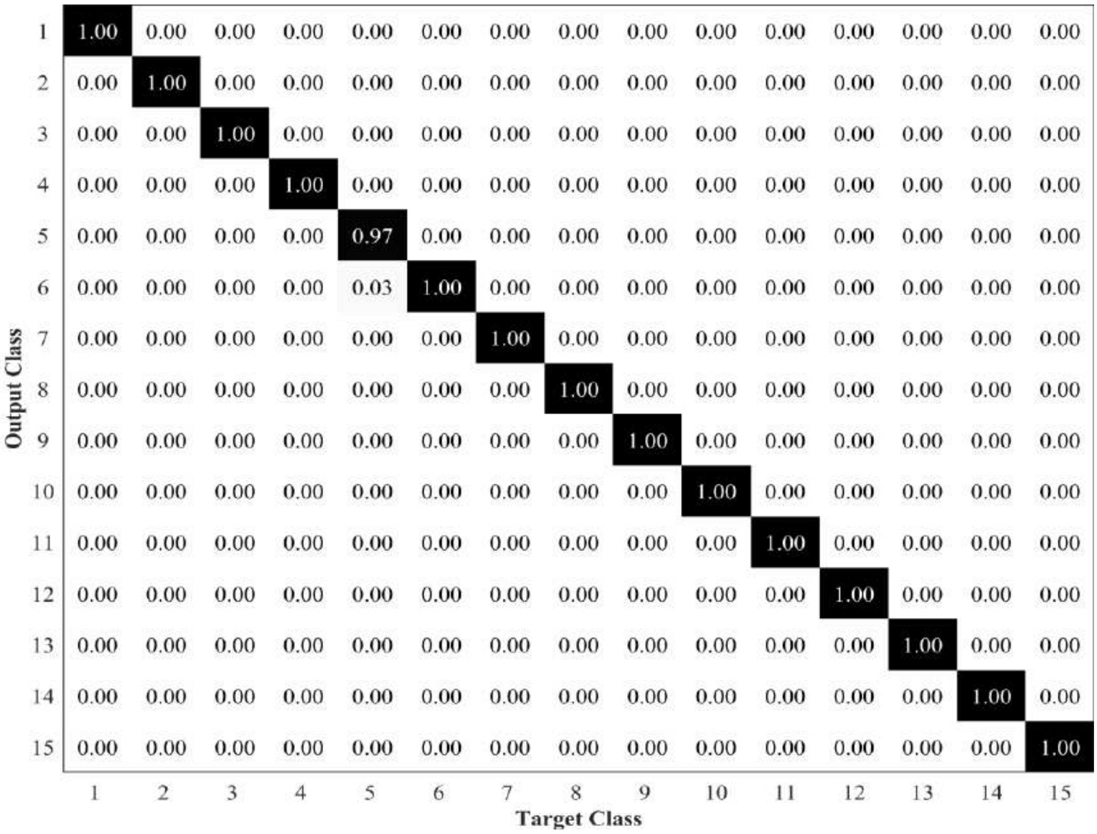
In Table 7.2. AUC aims to confirm that the probability of classifying a randomly chosen positive instance is higher than a randomly chosen negative one.

Table 7.2 : The obtained TPR, FPR and AUC using different approaches.

	Flavia			Swedish		
	TPR	FPR	AUC	TPR	FPR	AUC
SVM	94.29% ± 6.81%	0.18% ± 0.17%	99.90%	99.23% ± 1.70%	0.05% ± 0.12%	99.98%
NB	97.51% ± 3.12%	0.08% ± 0.12%	99.96%	97.25% ± 4.81%	0.20% ± 0.41%	99.90%
LDA	90.33% ± 9.16%	0.33% ± 0.46%	99.79%	99.42% ± 1.62%	0.04% ± 0.12%	99.97%
SVM+NB+LDA combined with NB	98.12% ± 2.14%	0.06% ± 0.07%	99.97%	99.80% ± 0.75%	0.01% ± 0.05%	99.99%

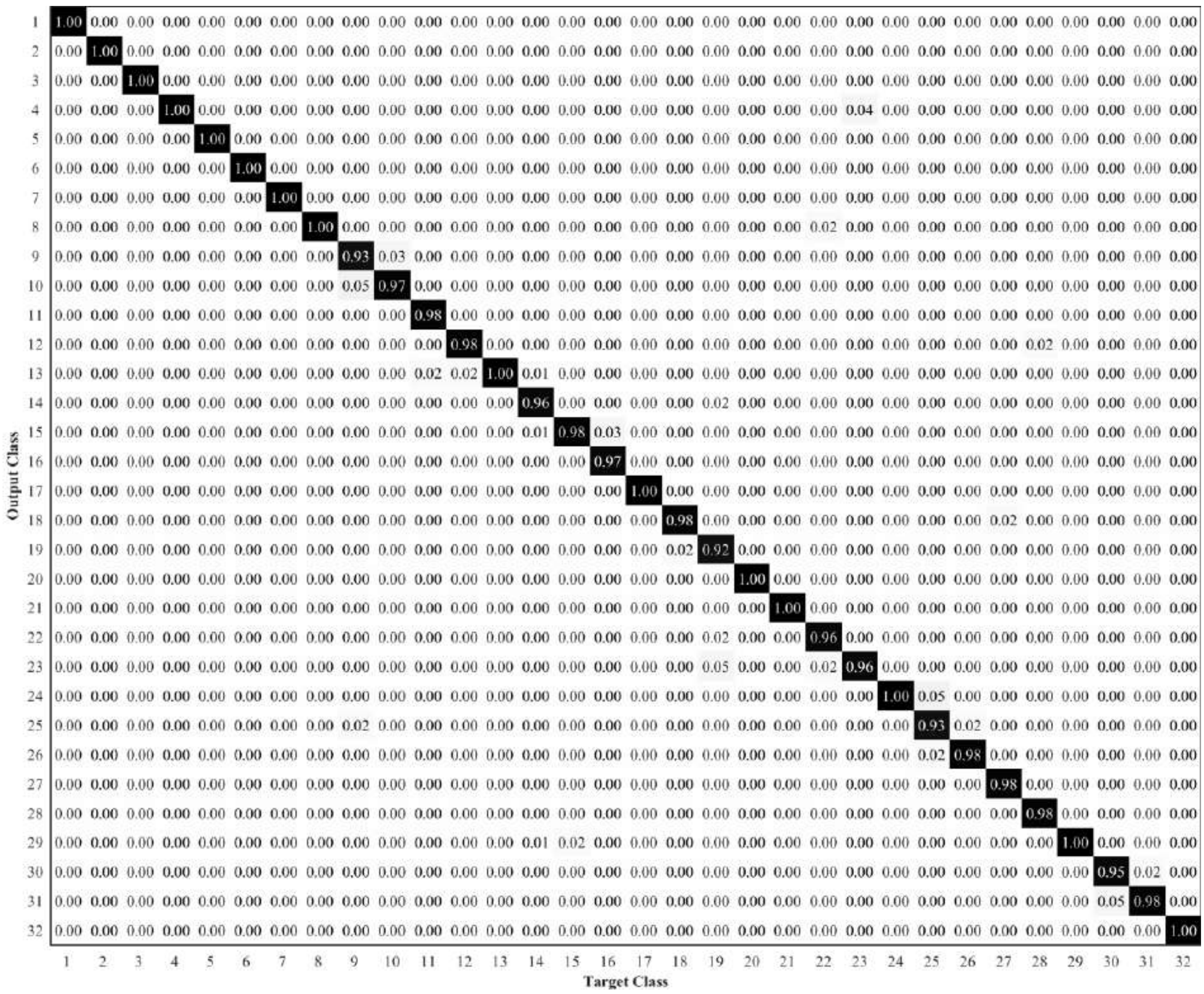
Table 7.2 and Figure 7.6 demonstrates that the adopted method consistently outperforms the single-classifier-based methods in all possible FPR/TPR. We have noticed that one classifier may perform well with one species but it fails with the others, especially those having high geometric correspondence. This issue could be tackled by combining multiple classifiers at a decision stage which increases the classification confidence. The obtained results validate the complementary effect and prove the superiority of the proposed approach.

Regardless of the high performance it yields; our method seems to occasionally confuse some leaf species. To discover the reason behind this confusion, we have to analyze the results in more details. To this end, we have generated the confusion matrices from Flavia and Swedish dataset separately. The obtained confusion matrices are presented in Figure. 7.7.



Output Class
Target Class
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
1 1.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
2 0.00 1.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
3 0.00 0.00 1.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
4 0.00 0.00 0.00 1.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
5 0.00 0.00 0.00 0.00 0.97 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
6 0.00 0.00 0.00 0.00 0.03 1.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
7 0.00 0.00 0.00 0.00 0.00 0.00 1.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
8 0.00 0.00 0.00 0.00 0.00 0.00 0.00 1.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
9 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 1.00 0.00 0.00 0.00 0.00 0.00 0.00
10 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 1.00 0.00 0.00 0.00 0.00 0.00
11 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 1.00 0.00 0.00 0.00 0.00
12 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 1.00 0.00 0.00 0.00
13 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 1.00 0.00 0.00
14 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 1.00 0.00
15 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 1.00

(a)



(b)

Figure 7.7: Confusion matrices (a). Swedish, (b). Flavia.

As it is illustrated in Figure 7.7, the confusion matrix provides more details about the evaluation outcomes. As instance, we can see that for Swedish dataset, the misclassification occurs among the species (9/10), (19/23), (25/24) and (30/31) respectively, whereas for Flavia it occurs only between the species (5/6). By taking a closer look to leaf images belonging to these species we found out that some of their samples look visually identical in terms of color and shape. Figure 7.8. Shows representative samples of a high color/geometric correspondence between leaves belonging to different species.

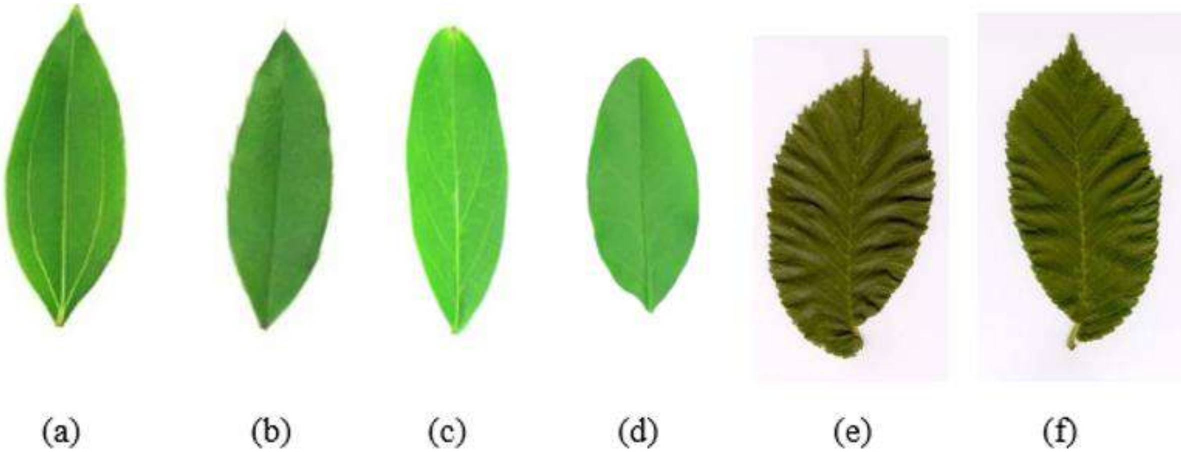


Figure 7.8 some samples from different species that look identical, From Flavia (a)/(b) and (c)/(d). From Swedish (e)/(f).

As it is illustrated in Figure 7.8, there are some leaves, from different species, that are highly similar or sometimes identical. Some samples are hard to be distinguished by the visual properties solely.

Experiment 2

In this sub-section, we aim to compare the proposed approach with other recent and relevant works on leaf classification. To do so, we opted for the Swedish dataset a configuration as in [29] we devote the first 25 images from each species for training, whereas the remaining 75 images are devoted for testing. Our comparison involved a variety of works that are interested in the morphological properties of leaves namely: inner distance (IDSC) [29], multiscale convexity/concavity representation (MCC) [164], Triangle-area representation (TAR) [165], Symbolic representation [166], shape tree [167], multi-scale distance matrix (MDM), and Triangle Side Lengths and Angle representation (TSLA). Several methods [[168], [16] have been also tested on the Flavia dataset, the same evaluation metric is used for evaluate the approach ten samples from each class is devoted for the test and the rest is for training. Table. 7.3 gives the results obtained by the involved works.

Table 7.3 : Obtained accuracies using shape-based features and our system.

Dataset	Work	Descriptor	Classifier(s)	Nb Feat	Accuracy
Swedish	[52]	(1)	1-NN	8[29]	97.6%
	[21]	MARCH	1-NN	101	97.33%

	[36]	TSLA	k-NN	2400	96.53%
	[20]	IDSC	SVM	12,288	94.13%
	[48]	SR		9600	95.47
	[19]	MDM	k-NN	16,384	93.60%
	[49]	STree		/	96.28%
	[47]	TAR	1-NN	8067	95.97%
	[46]	MCC		1280	94.75%
	Ours	Morphological	SVM+LDA+NB	**19**	**98.3%**
Flavia	[50]	(2)			98.40%
	[51]	(3)			96.50%
	[50]	GLC			95.00%
	[50]	MDM	K- NN	16,384	88.00%
	[11]	PNN	PNN	12	90.00%
	Ours	Morphological	SVM+LDA+NB	**19**	**99.06%**

As illustrated in Table 7.3, great efforts in literature have been done in order to reduce the error rate. The best accuracies that have been reported in related works were 97.3% and 98.4% for Swedish and Flavia respectively. However, our approach which is based on morphological features and parallel combination of multiple classifiers have highly reduced the error rate and yielded accuracies of 98.3% and 99.06% for Swedish and Flavia respectively even for recent works [169]. Another important factor of a successful recognition system is the response time. In contrast to other features such as MDM, IDSC...ect. Our method is based on a compact descriptor with a size of (19) that assures a very low response time which makes it suitable for mobile applications.

7.5 Conclusion

A fast and accurate automatic recognition system has been presented in this paper to tackle the challenging problems of automatic plant identification. The proposed system is based on a parallel combination of three classifiers namely LDA, NB and SVM with various combination techniques such as Max, Min, Product, Average, Sum, Majority Vote and Naïve Bayes. The performance of the system has been evaluated on two well-known leaf datasets namely, Swedish and Flavia. The outcomes have demonstrated the intuition telling that a decision made by multiple classifiers should outperform the one made by one single classifier. After conducting a comparative of several combination methods and evaluation against other leaf systems, the classification results have showed that NB has yielde the best results and the proposed system outperformed the others. Due to the employment of a highly compact leaf image descriptor, the response time yielded by our system is trivial compared to other systems based, which makes it suitable for mobile applications.

Chapter 8

8 Plant Leaves Recognition Based on a Hierarchical One-Class Learning Scheme with Convolutional Auto-Encoder and Siamese Neural Network

Contents

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Plant Leaves Recognition Based on a Hierarchical One-Class Learning Scheme with Convolutional Auto-Encoder and Siamese Neural Network

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Abstract: In this paper, we propose a novel method for plant leaves recognition by incorporating an unsupervised convolutional auto-encoder (CAE) and Siamese neural network in a unified framework by considering Siamese as an alternative to the conventional loss of CAE. Rather than the conventional exploitation of CAE and Siamese, in our case we have proposed to extend CAE for a novel supervised scenario by considering it as one-class learning classifier. For each class, CAE is trained to reconstruct its positive and negative examples and Siamese is trained to distinguish the similarity and the dissimilarity of the obtained examples. On the contrary and asymmetric to the related hierarchical classification schemes which require pre-knowledge on the dataset being recognized, we propose a hierarchical classification scheme that doesn't require such a pre-knowledge and can be employed by non-experts automatically. We cluster the dataset to assemble similar classes together. A test image is first assigned to the nearest cluster, then matched to one class from the classes that fall under the determined cluster using our novel one-class learning classifier. The proposed method has been evaluated on the ImageCLEF2012 dataset. Experimental

results have proved the superiority of our method compared to several state-of-the art methods.

Keywords: plant leaves classification; hierarchical classification; Siamese neural network; convolutional auto-encoder; one class learning.

8.1 Introduction

Plants have a significant impact on human life and development; without them, there will be no existence of the earth's ecology [138]. Plants play a decisive role in providing oxygen, clean air, food, etc. Additionally, they contribute to several tasks of scientists from different domains such as agriculture, medicine, and environmental fields.

Traditionally, botanists classify plants manually by using molecular biology and cellular features of leaves. Nevertheless, with the huge number of plants that exist on the earth classification through experts and botanists is subjective and requires much effort from experts. Besides, this process is too expensive in terms of time and effort.

On the contrary, with the development of computer software and hardware, mobile devices, and image processing. Automatically performing such a task, using machine learning techniques, is rapid, inexpensive, and accurate as well. Automatic plant identification has become a hot research topic in recent years.

Plants can be classified using their organs such as leaves, stems, fruits [170], [171] or flowers. Nevertheless, the leaf is the most adopted part for recognition purposes since it carries out the plant's inherent properties and it is available all the seasons, contrary to the other parts. In addition, the leaf flatness makes it easy to represent it by machine.

In the literature on this subject, many researchers have attempted to put forward systems that are capable of automatically identifying plant species based on leaf images. Some approaches have resorted to handcrafted features, such as shape, for describing leaves [119] ,[172] and texture for describing the veins [125] , [72] or by the combinations of both [58]. Some others have tackled the problem by introducing special discriminative plant leaf features [173] (or domain knowledge) that are based on botanical characteristics. In general, handcrafted features are defined manually and extracted through instructed algorithms. However, as a matter of fact, this process is complex and requires changes and recalculation for each problem or data set.

Recently, with the impressive performance of deep learning, neural networks can learn essential characteristics directly and automatically from raw images. Deep learning approaches have been successfully applied in solving different issues including facial expression recognition [174], medicine classification [175], and plant identification[176].

Despite the considerable efforts that have been undertaken by researchers, automatic plant identification from leaf images is still an open issue, and there is room for improvement.

In this paper, we put forward a novel hierarchical method for automatic plant leaves recognition based on a novel classifier that consists of incorporating Siamese as an alternative to traditional loss within a convolutional auto-encoder (CAE). We consider a one-class learning strategy, in which a CAE is trained for each class. For a test image from class #N, the loss yielded by the class N's auto-encoder is supposed to be much smaller compared to the losses produced for the other classes. However, this raises another issue since the CAE trained on complicated leaf images is capable of perfectly reconstructing those relatively easier images from different classes. To handle such an issue, we propose training a Siamese on top of each CAE (i.e., the CAE of each class). This one-shot learning strategy (i.e., SCNN) is considered as intelligent loss, which is an alternative to the conventional CAE loss. Siamese is integrated to learn symmetric/asymmetric between images belonging to the same class and those from different classes, respectively.

Plants are organized in a hierarchical order (i.e., family, genus, and species). According to the literature, hierarchical plant classification applied by the relevant methods [96], [177] consists in assigning test images (first to the coarse classes and then to the fine classes) by progressing through the plant's hierarchy (i.e., genus, and species). Nevertheless, this process requires pre-knowledge of the dataset being classified, which is actually difficult to do, especially for non-experts. In this paper, we propose a hierarchical classification scheme that doesn't require pre-knowledge, and which can be used by non-experts. Our scheme consists in clustering the entire dataset to gather symmetric classes together. A test image is first assigned to the most suitable cluster using a clustering algorithm and then matched to one class from the classes that fall under the detected cluster by using our novel one class learning classifier (i.e., CAE based on Siamese as an alternative loss).

The evaluation of the proposed method was carried out on a well-known dataset, namely ImageCLEF2012. Experimental results have demonstrated the efficiency of our method and a noteworthy performance has been reached compared to certain other methods. The remainder of this paper is organized as follows. A brief review of related work is presented in Section 2. In Section 3, we describe the details of the proposed method. The experimental results are presented in Section 4. Finally, we draw some conclusions for future work.

8.2 Related Work

In recent years, a lot of effort has been made to achieve more reliability in automatic leaf recognition. From the literature, two main approaches have been considered: plant classification based on hand-designed features using a classifier and deep learning strategies. For the first one, features are chosen manually and extracted through instructed algorithms, then only a subset of the most discriminant features are considered the obtained handcrafted features are used to train classifiers (SVM, NN, NB, etc. [7]). For the second one (i.e., deep learning), it can learn discriminative characteristics from the raw images and recognize them automatically.

As instance for the hand crafted features, Hu et al. [32] proposed a contour-based shape descriptor named the multi-scale distance matrix (MDM) for fast plant leaf recognition. They used the matrix for pairwise distances between points sampled on the boundary of a leaf to capture the geometric structure of the shape, and 1-NN in the classification stage. In [34], Wang et al. proposed a method that uses a multi-scale arch height (MARCH), where the hierarchical arch height features at the K-scale are extracted from each contour point to capture concave and convex characteristics. This method provides a coarse-to-fine shape description of the leaf. The recognition rate was calculated using the 1-Nearest-Neighbor classifier, and a prototype system for online plant leaf identification was developed to be used on a mobile platform. The authors in [116] proposed to represent the leaf contour using two matrices. The first one is the sign matrix to extract the convex and concave features, and the second one is the triangle center distance to extract the spatial properties of the contour; the 1-NN is used for recognition.

Although leaf shape may be adequate to distinguish between some species, the shapes of others may be highly symmetrical, making differentiation difficult. Such a problem could be solved by taking additional leaf features such as texture and veins. According to [178], GLCM and Gabor wavelet are the most commonly used texture features. Typically, as in [173], wavelets have been used to decompose images, fractals to extract features, and artificial neural network to classify leaf images. Ghasab et al. [149] used texture features derived from GLCM, namely contrast, correlation, energy, homogeneity, and entropy, and combined them with shape, color, and vein features. In [60], Kadir et al. built foliage plant identification systems. Zernike moments were combined with other features (namely geometric features, color moments, and gray-level co-occurrence matrix (GLCM)). The results show that Zernike Moments have a prospect as features in leaf identification systems once they are combined with other features. In [49], a modified local binary pattern was proposed to extract texture features, and a simple nearest neighbor classifier was performed for classification, to decrease the intra-class variation the clustering was exploited in order to group symmetric leaf samples; the results prove that considering texture features alone is not sufficient. In [76], the authors propose to classify plant species using 19 leaf venation features using a support vector machine (SVM) with an RBF kernel. In [77], the authors propose to identify plant leaf based on visual features using different artificial intelligence techniques such as Artificial Neural Networks, the naive Bayes algorithm, the random forest algorithm, the K-Nearest Neighbor (KNN), and the Support Vector Machine (SVM). The best results were carried by SVM. In [78], the authors propose morphological features and the support vector machine (SVM) with an adaptive boosting technique to classify plants.

Despite the effectiveness of the handcrafted features in the plant classification system, such features are limited to specific conditions, if the characteristics of the images change (e.g., over space or time), then the performance of these algorithms significantly decreases. In the last few years, to overcome the drawbacks of existing approaches, deep learning methods have proved to demonstrate significant success in several plant identification systems.

For instance, in [179], the authors proposed a CNN model for plant leaf classification (Leaf-Net). The model was carried on three public datasets. The results prove that CNN outperformed the hand-crafted method. In [102], the authors recognized leaf image at different scales. Images are first down-sampled into multiples low resolution images. Then, in order to learn different characteristics in various layers, the MSF-CNN is proposed. The final feature is obtained by fusing all the last layer information. The classification is performed using either a support vector machine (SVM) or multi-layer perceptron (MLP) classifier. In [71], Lee et al. designed a hybrid feature extraction models for plant identification based on de-convolution neural network. They attempted to analyze how CNN learn directly features from the raw representations of an input image. Their main conclusion was that veins are the best representative features compared to those of outline shape. Ghazi et al. [98] analyzed the influence of different parameters, such as batch size and number of iterations, on the performance of the different deep learning architectures, including Google-Net, Alex-Net, and VGG-Net. They revealed that the number of iterations was the most significant factor that affects fine-tuning performance, whereas data augmentation comes in the second place. In [180], the authors proposed to identify leaf species by fine-tuning the Alex-Net.

In [96], the authors present a fine-grained plant leaf classification method based on the fusion of deep models. The basic idea consists of the adoption of hierarchical classification strategies by using two levels of CNN. In the first level, global features are extracted, while in the second one, local features are considered. The fusion of the hierarchical levels is conducted using a coarse-to-fine strategy (i.e., the predicted coarse categories (i.e., genus) are used to define which subordinate category will be evaluated during the fine prediction (i.e., species)). Similarly, in [177], the authors also proposed two representations as in the previous work, albeit by considering Siamese at each level to overcome unbalanced and scalable problems. In [104] they performed a comparison between Siamese and CNN for plant species identification with small datasets. Their conclusion is that the Siamese performed better than CNN in terms of lower computational cost and can generalize better than CNN.

Despite the improvement brought by deep learning in plant recognition, most methods exploit it as a feature extractor whilst it has several properties that can be introduced to improve and give reliable results. Furthermore, according to the literature, most methods treat plant identification as a flat classification problem, whereas plant hierarchical organization may serve to accelerate and facilitate the identification process as well as reduce the problem of inter-species.

8.3 Proposed Method

In this section, we give details on the proposed method for plant leaves recognition. In this work, we propose a hierarchical plant classification system based on one-class learning scheme with convolutional auto-encoder and Siamese neural network. The hierarchy of our system consists mainly of two steps (clustering and classification). Figure 8.1 presents a Hierarchical classification scheme followed by the proposed method.

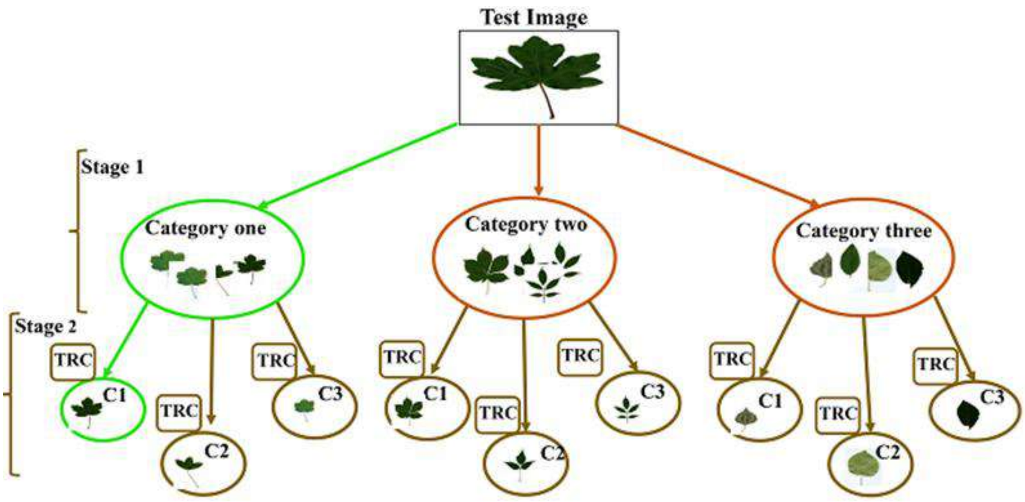


Figure 8.1 : presents a Hierarchical classification scheme followed by the proposed method. (stage1: clustering, stage2: classification using our novel method (classifier), TRC: the trained novel classifier, C: the classes).

Through this section, we first show the general pipeline of our novel classification scheme that is based on one-class learning strategy based on a convolutional auto-encoder using a Siamese neural network as an intelligent loss. Then, we present details on each step, and at the end of this section, we will provide the general strategy of our hierarchical scheme**.**

8.3.1 General Pipeline of the Novel Classifier

In the proposed plant classification system, each image I_i is labeled with a label from the set $= \{i \;/\; i = 1, \dots, n\}$, where n stands for the number of classes. For each class c_i we design a convolutional auto-encoder, denoted as CAE_i. Images within class c_i are firstly fed to the encoder to generate the latent representation termed as R $(I_j \rightarrow R)$, then the decoder reconstruct the code R to produce the reconstructed image I'_j $(R \rightarrow I'_j)$. On the top of each CAE_i, a Siamese is integrated as an indicator for the class to which an image sample belongs. After training CAE_i for each class, $Siamese_i$ is trained using positive examples (represent images I_i and its reconstructions I'_i generated by the trained CAE_i) and negative examples (represent images I_j and its reconstructions I'_j generated by the trained $CAE_i/(j \neq i)$). The

Siamese is an efficient alternative of the conventional loss of CAE_i. This one-class strategy is repeated for all of the remaining classes.

To sum up, hereafter, we summarize the steps of our method

In the first step, the unsupervised CAE of each class c_i (from the set of classes = $\{i \ / \ i = 1, \dots, n\}$) is trained separately using images of c_i . Figure 8.2 presents the flowchart of the first step.

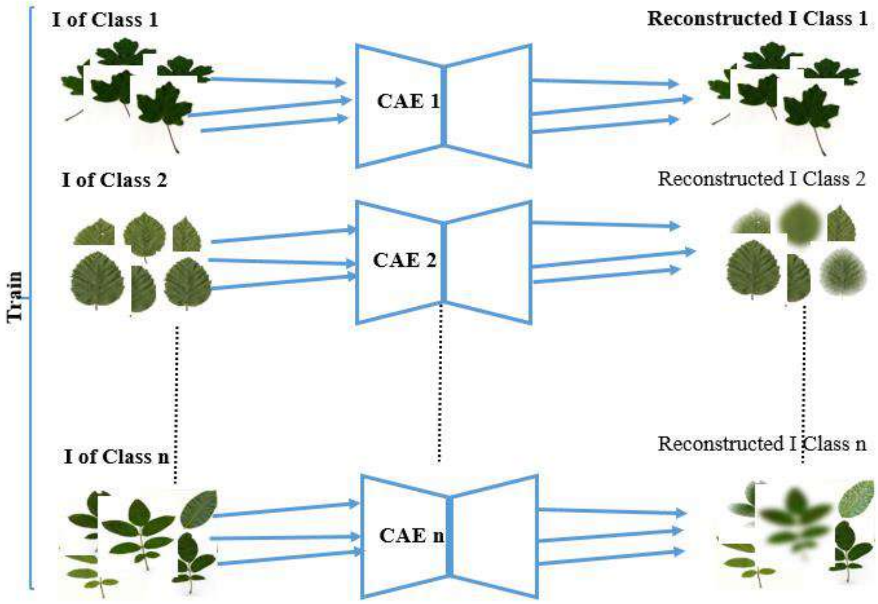


Figure 8.2 : Flowchart of the first step.

In the second step, images intended to be used for SCNN training are generated. For each class, original images, their respective reconstructed versions are serve as positive examples as well as randomly selected images from other classes (i.e., other than the concerned class) and their respective reconstructed versions serve as negative instances, are prepared. Figure 8.3 presents the flowchart of the second step.

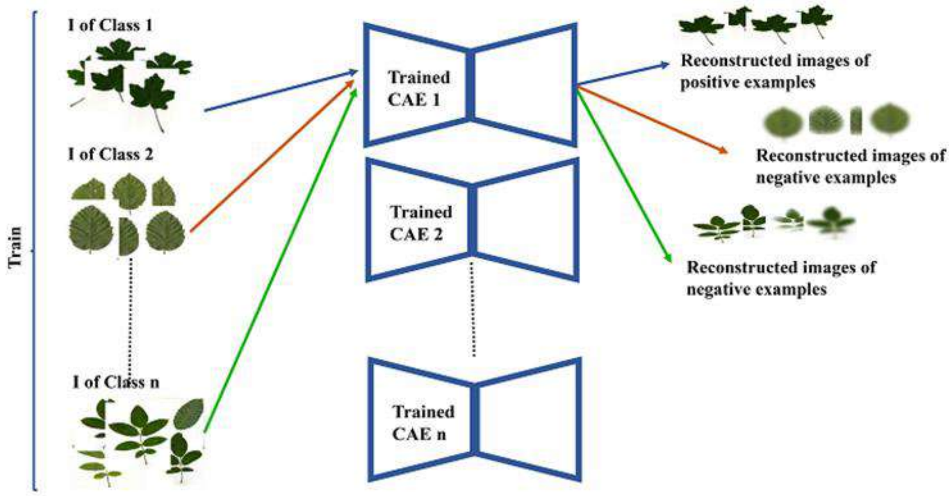


Figure 8.3 : Flowchart of the second step.

In the third step, Siamese is trained using positive and negative instances prepared in the previous step. (Where the size of negative and positive examples that are fed to train Siamese is equal). Figure 8.4 presents the flowchart of the third step.

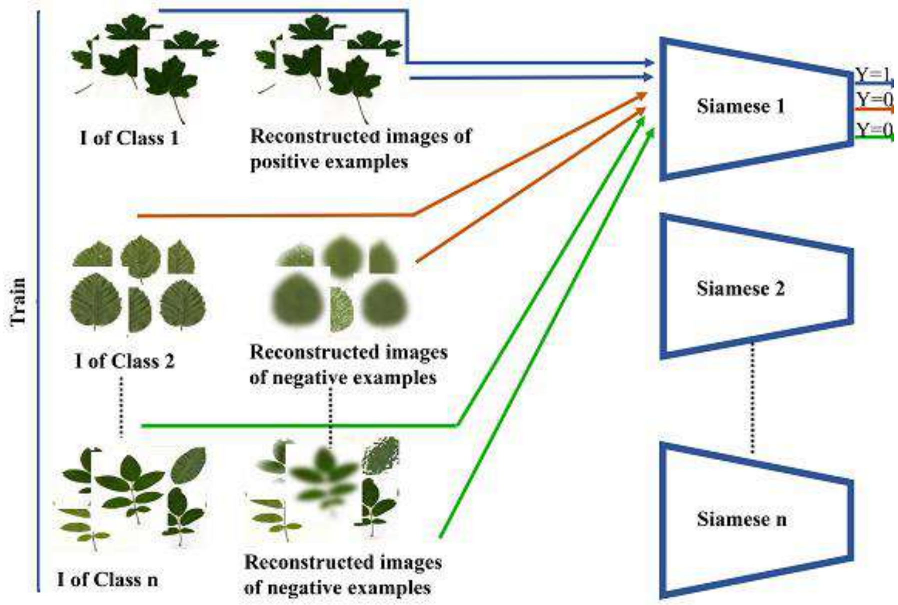


Figure 8.4 : Flowchart of the third step.

For a new probe p to be classified, a confidence score is generated for each class c_i by feeding p to $CAE_i + SCNN_i$. In particular, p is passed by each CAE_i to generate its reconstructed version p'. It is expected that once p and p' are passed. By the actual class (i.e., the class to which p belongs), a high similarity score will be yielded by the$SCNN$.

On the contrary, passing by other classes yields low similarity scores that are near to zero. A p is assigned to the class having obtained the maximum confidence score.

To speed up computations and reduce more the problem of inter species, we have opted for a hierarchical classification fashion by reducing the classification space based on clustering images from different classes using K-means [181]. For a test image, it is first mapped to the most appropriate cluster then matched solely with classes that belong to the selected cluster using our novel classifier (CAE base on Siamese as a loss). Figure 1 presents the two stages that the image feeds into our system.

8.3.2 Network Architecture and Loss Function

In our work, we have dealt with a convolutional auto-encoder that has been successfully applied to the computer vision domain. The convolutional auto-encoder is a subset of convolutional neural networks. They are similar, but the difference between them is that the weights in the CAE are shared among the inputs, preserving the spatial locality. Due to the use of CNN's integrated properties, some specific layers, such as convolutional, pooling, and so on, aid in feature extraction. Each convolution operation represents a filter that learns how to extract a specific plant feature by using filters. Following the convolutional operation, a pooling layer is usually included. The pooling layer reduces the input data's dimensionality.

In our work, for each class c_i we have designed a convolutional auto-encoder CAE_i, images within the class c_i are first fed to the encoder to generate the latent representation $(I_j \rightarrow R)$ through a series of convolutional and max-pooling layers, then second to the decoder with a series of de-convolutions and un-pooling layers to reconstruct the code$(R \rightarrow I'_j)$.

1. Convolutional Auto-encoder Architecture:

It consists of four convolutional blocks: convolutional layer with 8 filters with 10 × 10, Relu activation function, and max pooling layer; convolutional layer with 16 filters with 5 × 5, Relu activation function, and max pooling layer; convolutional layer with 32 filters with 3 × 3, Relu activation function, and max pooling layer; convolutional layer with 64 filters with 3 × 3, Relu activation function, and max pooling layer; and finally the Dense layer. Since we have to deal with CAE as a binary classifier (one class learning), the binary cross-entropy is used as a loss function (Equation (1)):

$$BCE(y,p) = -y.log(p) - (1-y).log(1-p) \tag{1}$$

Where y is the original image that we present to the AE and p is the reconstructed image obtained by the AE. For the decoder we have used de-convolutional and un-pooling layer it performs the inverse operation of the convolution layer and pooling layer. The network has symmetric architecture, with the same number of layers and feature maps generated in each layer in both parts.

Figure 8.5 gives an overview of CAE architecture. As it can be seen, this CAE is trained for class a which it could reconstruct images from this class well, on the contrary images from other classes ($eg;\ b$) can't be well reconstructed since it is not trained for.

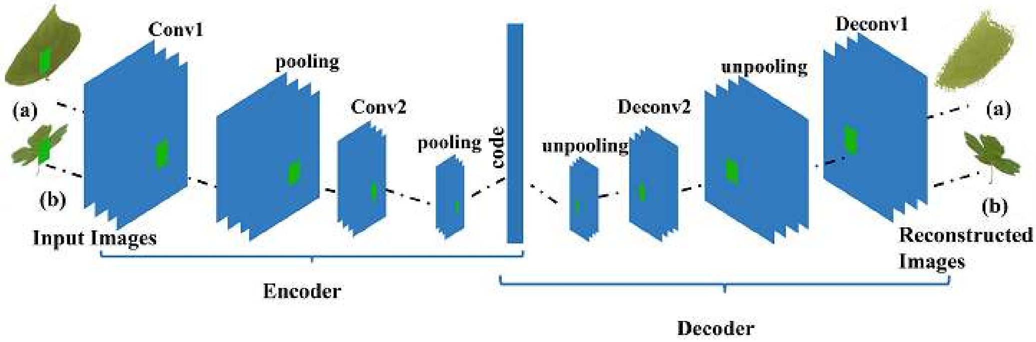


Figure 8.5 CAE architecture.

2. Siamese Convolutional Neural Network Architecture, Loss Function:

A Siamese neural network consists of two or more sub-networks that accept different inputs but are linked at the top by an energy function. A Siamese CNN consists of two symmetrical CNN neural networks both sharing the same weights and architecture. The objective of the Siamese network is to learn whether two input values are similar or dissimilar. Each CNN receives an input image, which is then processed through a series of convolutional and max-pooling layers. The last volume containing the extracted features is flattened into a 1D vector of features. A connected function will be used to connect the two vectors extracted by the convolutional neural network.

In our work on the top of CAE, we integrate a Siamese, which consists of two CNN as sub-networks of two convolutional blocks: convolutional layer with 32 filters with 10 × 10, Relu activation function, and max-pooling layer; and convolutional layer with 64 filters with 7 × 7, Relu activation function, and Max pooling layer. The units of this convolutional layer are flattened into a single vector using global average pooling. This vector is then connected to a fully-connected layer (FC) with 4096 neurons. In order to merge the obtained two vectors L1 is used, from [182] the L1 distance since it is better than the L2 distance for Siamese based on CNN. A final dense layer (fully connected layer) with a sigmoid activation merges all the values into a single vector and produces the similarity or dissimilarity response. The dense layer computes a weighted sum of the vector's values (Equation (2)).

$$y = \sum_{i=1}^{N}(W_i \times X_i) + b \qquad (2)$$

Where $W_i/(i = 1, \dots, n)$ represent the weights of the synapses of the dense layer; X_i $(i = 1, \dots, n)$ represent the elements of the merged vector achieved from l_1 (Equation (3)).distance.

$$l_1 = (|X_{11} - X_{21}|, |X_{12} - X_{22}|, \dots \dots \dots, |X_{1n} - X_{2n}|) \quad (3)$$

Where X_1 and X_2 are the two vectors obtained from the two CNN; n represent the number of elements in each vector.

Then it adds a bias value to it and applies the sigmoid (σ) function (Equation (4)) to this value. The outcomes are in the interval of [0, 1]. The cross-entropy (Equation (1)) is exploited for training the network.

$$\sigma(y) = \frac{1}{1 + e^{-y}} \quad (4)$$

Figure 8.6 gives an overview of SCNN architecture. As it can be seen, this SCNN is trained on negative examples (images from class (b) and its reconstruction from CAE Figure 8.3) and positive examples (images from class (a) and its reconstruction from CAE). Siamese is trained with the output of y = 1 for positive examples and y = 0 for negatives.

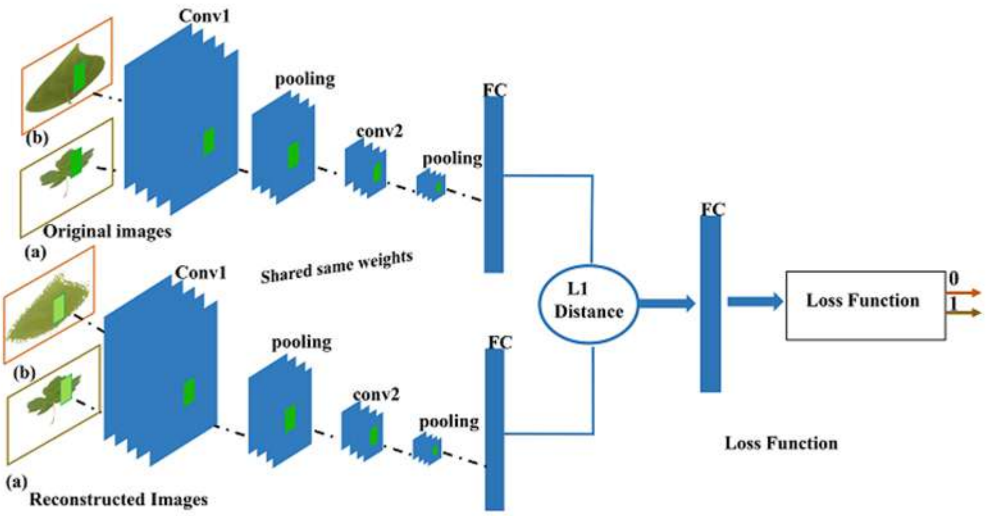


Figure 8.6 : Siamese architecture.

The integration of the two architectures presents our novel classifier that is based on CAE Using Siamese neural network as an alternative loss. Figure 8.7 present the architecture of our novel classifier.

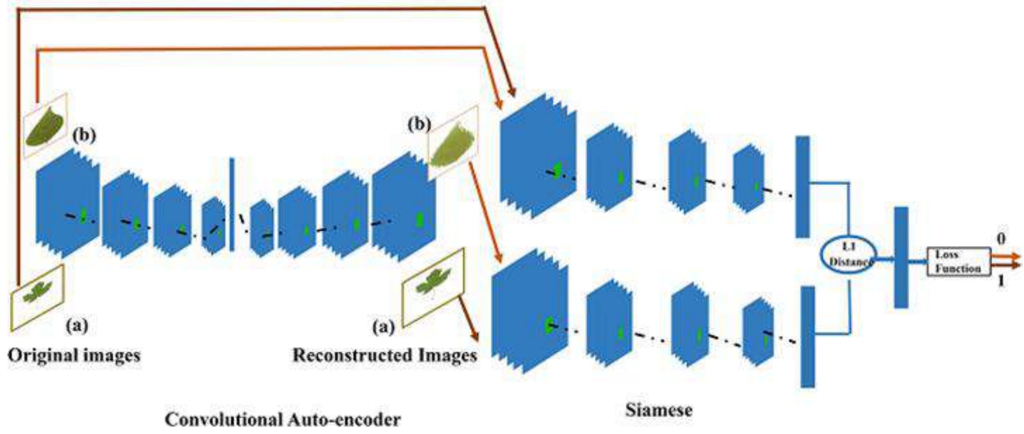


Figure 8.7 : Novel classifier (CAE based on Siamese as a loss) architecture.

8.3.3 Rationality of the Proposed Method

The main novelty in this work lies in considering a one-class learning strategy, where CAE and SCNN are integrated into a unified framework. Indeed, it is well-known that au-to-encoder is an unsupervised network that is mainly used for dimensionality reduction and features learning. However, in our case, we extend it to a supervised scenario by considering loss values produced by each class. In particular, an auto-encoder is trained for each class separately, and the loss value is considered as an indicator of the class to which a test sample belongs. If a test sample is reconstructed for a class A with loss equals to x, and for class B with a loss equals to y, and x < y, then we can assign the sample to class A. Nevertheless, the CAE trained on complicated leaf images is eligible to punctually recon-struct those of relatively easier images from other classes. To overcome this problem, we propose using the Siamese neural network (Siamese for each class) as an intelligent loss metric on top of each CAE to alleviate the shortcomings of conventional loss. For the sake of illustration, the Siamese network of class 1 is trained using negative and positive ex-amples, where positive is the original leaf image from class 1 and its reconstructed image, and the negative one is an image from other classes and its reconstructed one by the CAE of class 1. For a test image that is from class 1, as SCNN1 is trained on maximizing confi-dence score for original images from class 1 and their respective reconstructed versions (minimize the score for images from other classes, respectively), passing by CAE1 (+ Siamese 1) will almost produce a high similarity score. For another test sample from a class different than class 1, CAE1 (+ Siamese 1) will produce a low similarity score, as SCNN1 is trained to do so. As for testing strategy, some relevant works [96], [177] have considered a hierarchical classification procedure, wherein classification is firstly performed for the coarse classes, and then passed to the subsequent levels in the hierarchy (i.e., genus, species). However, this procedure requires pre-knowledge of the dataset being classified, which is predominantly not possible. Thus, using those methods is limited to persons with knowledge of this field (i.e., experts). In this work, however, we adopt a hierarchical classification scheme that doesn't require this pre-knowledge, making it feasible to em-ploy our method by non-experts. We cluster the whole dataset using K-means, such that each class falls exactly in one cluster. For a test image, instead of performing matching with all classes, it is mapped to the most appropriate cluster then matched only with classes that fall under the detected cluster. This permits a reduction in the classification space, and thus speeds up the recognition process.

8.4 Experiment

This section is devoted to evaluating our proposed approach under different condi-tions. In addition, we conduct a comparative evaluation against other recent works in order to prove the effectiveness of our method.

8.4.1 Dataset

ImageCLEF2012 leaf dataset: this dataset was created as part of the Pl@ntNet project. Images are collected from Western European regions. ImageCLEF2012 is one of the most challenging datasets due to its richness in terms of leaf categories (compound and simple realistic), species, variability, and similarity between species. As well as, differences on the acquisition level in terms of period, location and person. ImageCLEF2012 contains three types of images which are: scan, scan-like and photograph. The scan images have a white background, scan-like are images with minimal shadowing, and the photograph images are captured in nature with an uncontrolled manner. In our experiments, we have considered the scanned images, which represent 57% of the total database. There are 6630 imag-es in this subset; 4870 in the training set are from 115 species and 1760 in the test set are from 110 species. Each class contains between 2 and 249 images. Figure 8.8 depicts representative samples from the ImageCLEF2012 scan dataset.

Figure 8.8 : Representative samples from ImageCLEF2012 scan dataset.

8.4.2 Results

In this section, we will provide the results of our experiments. In all of the experiments, we have used the same protocol of the ImageCLEF2012 scan dataset. Approximately 4870 images are for training and 1760 images are for testing. From the training set, we have set 80% for training and 20% for validation, and the data augumentation technique was used to train the autoencoder neural network.

1) Experiment 1: Measuring the Processing Time

As previously explained, the proposed model is made up of two components namely unsupervised convolutional auto-encoder (CAE) and the Siamese convolutional neural network that replaces the conventional loss function. The target of this experiment is to demonstrate that our model can converge rapidly, and Siamese doesn't require a high processing time. The Siamese curve of train and validation accuracy of class one of the first category are presented in the Figure 8.9.

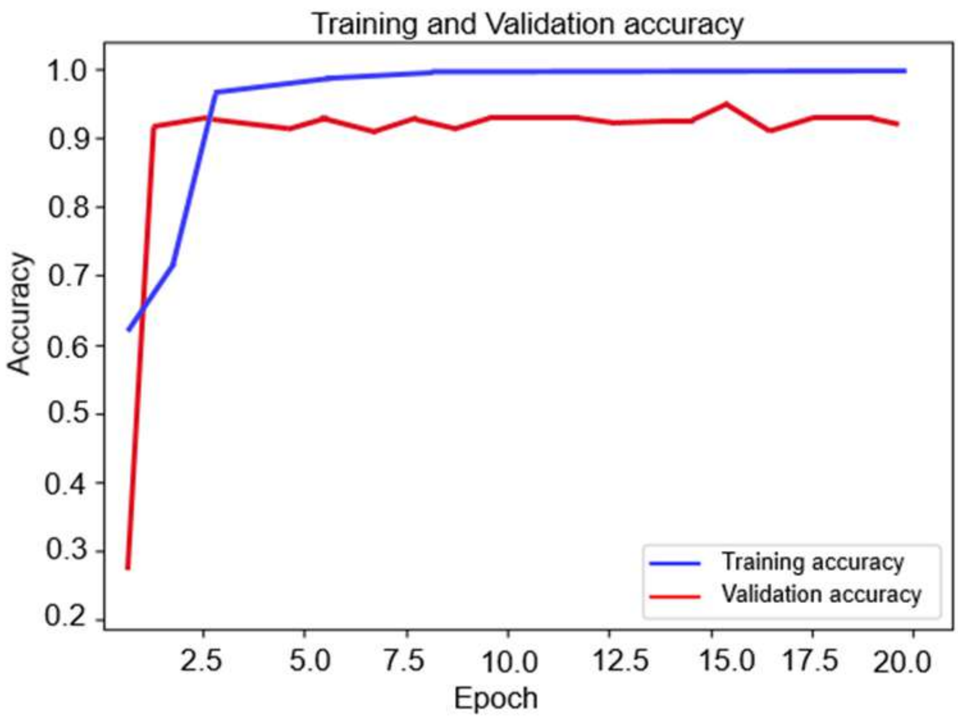
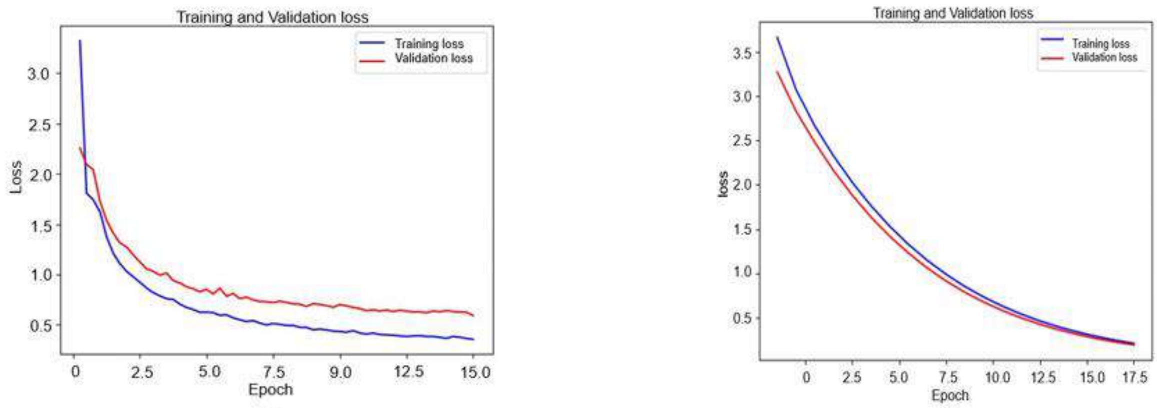


Figure 8.9 : Training and validation accuracy curves.

As can be seen from the two curves, our model can converge very quickly in more than 95% with only a few epochs. For example, at three and five epochs, the model achieved 93%

and 94% for validation, respectively, and 96% and 97% for training, respec-tively. This proves that our system does not require a high processing cost and can learn to predict in a very short period of time.

To demonstrate that SCNN has improved our model and that it converges faster than a model based solely on CAE. The training and validation loss of CAE and Siamese are depicted in Figure 8.10. As can be seen in the first epoch, the CAE's loss for training is 34% and 30% for validation that is higher than the loss of SCNN which is only 21% for training and for 22% validation, two epochs after the SCNN has a training loss of 0.8% and a validation loss of 10% that is lower compared to 18% and 16% of the CAE's training and validation loss. From the curves, SCNN proves that it has improved our model and doesn't require a high processing time.



(a) (b)

Figure 8.10 : Siamese and CAE loss training and validation curves: (a) Siamese and (b) CAE.

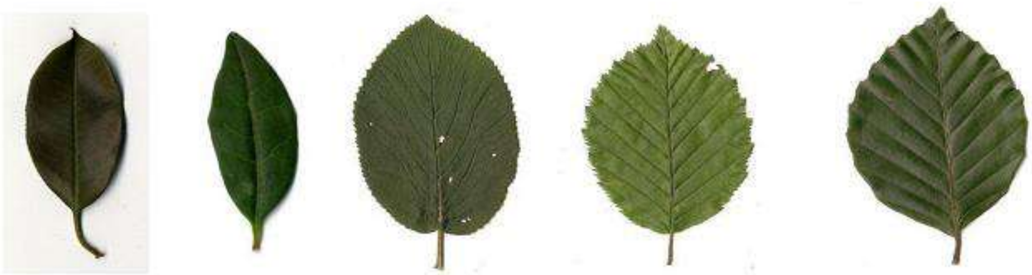
2) Experiment 2: Confusion Matrix

Regardless of the high performance that yields our method, it seems to occasionally confuse some leaf species. To discover the reason behind this confusion, we have to analyze the results in more detail. To this end, we have generated the confusion matrix of one category that contains 17 classes. The obtained confusion matrix is presented in Figure 8.11.

1	**14**	0	1	1	0	0	4	4	4	0	0	0	0	2	0	3	0
2	0	**3**	0	1	1	0	5	2	0	0	0	0	0	1	0	0	0
3	0	0	**0**	0	0	0	0	8	0	0	0	1	0	0	0	0	0
4	0	0	0	**7**	1	0	0	0	0	0	0	0	1	0	0	0	0
5	1	0	0	1	**4**	2	0	4	0	0	2	1	0	0	1	1	0
6	0	0	0	0	0	**4**	0	0	0	0	0	0	0	0	2	0	0
7	0	2	0	0	0	0	**6**	3	1	0	0	0	0	0	0	0	0
8	1	0	0	0	0	0	0	**10**	0	0	0	0	0	0	0	0	0
9	0	2	0	1	1	0	2	2	**1**	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	1	0	**19**	0	0	0	0	0	0	0
11	0	0	2	1	0	2	1	0	0	0	**3**	0	0	0	2	1	0
12	0	0	0	0	0	0	0	1	0	0	0	**8**	0	0	2	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	**7**	0	3	0	0
14	1	0	0	0	0	1	0	0	1	0	0	0	0	**10**	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**11**	0	0
16	0	0	1	13	1	0	1	0	0	0	0	0	2	0	0	**1**	1
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17

Figure 8.11: Confusion Matrix.

As it is illustrated in Figure 8.11, the confusion matrix provides more details about the evaluation outcomes. For instance, we can see that misclassification occurs among the species (21/41), (57/71), and (122/21) respectively. By taking a closer look at leaf images belonging to these species, we found out that some of their samples look visually identical in terms of color, veins and shape. Figure 8.12. Shows representative samples of a high color/geometric symmetry between leaves belonging to different species.



Class 71 Class 57 Class 41 Class 21 Class 122

Figure 8.12: Representative samples of a high color/geometric correspondence between leaves belonging to different species.

3) Experiment 3: Comparison with State of the Art

In this sub-section, we aim to compare the proposed approach with other recent and relevant works on leaf classification. To do so, we opted for the ImageCLEF2012 dataset a configuration as in [116]. This subset contains 4870 leaf images for training and 1760 leaf images for testing. The performance evaluation standard employed was the same as [116].

Our comparison included a number of studies that were interested in leaf species and in the ImageCLEF2012 dataset. Figure 8.13 presents curves that give the results obtained by our novel method and the works involved.

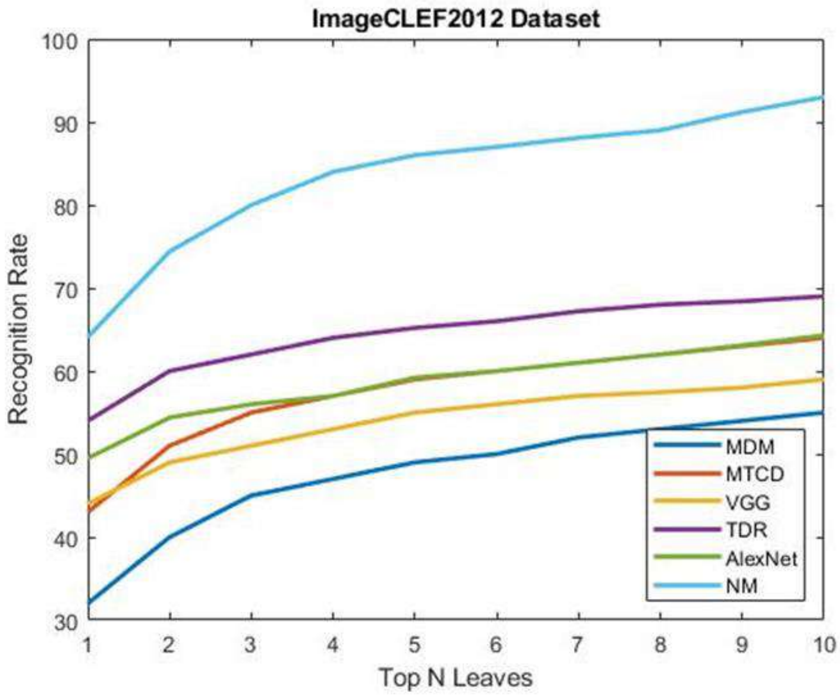


Figure 8.13 : Recognition results on scan category of ImageCLEF2012 leaf Dataset.

Since we have dealt with categories and in order to get the final curve of the proposed method, we have first obtained the top ten of each category then, the sum of them represent our final curve. From the results, we can observe that our Novel Method (NM) Convolutional auto encoder based on Siamese achieves the best recognition performance among all of the competing methods in only the top ten. The recognition rate of our novel method is much higher compared to the deep learning methods VGG16 and Alex-Net [116], and the recognition accuracy of our method is higher than that of the two networks by 20% and 13%, respectively in just the top one. For the handcrafted methods, our system has also yielded very good results compared to that of the MDM [32], MTCD [119], and Triangle-Distance Representation [116] methods (TDR); our system is higher than the mentioned methods by 22%, 21%, and 10%, respectively, when only one candidate result is considered. These results indicate that the proposed approach using hierarchical methods based on one class learning techniques can distinguish dif-ferent plant species very well. Furthermore, our novel system is well suited for large-scale images.

8.5 Conclusions

An accurate hierarchical automatic recognition system based on a novel one-class learning classifier has been presented in this paper. In contrast to the conventional exploitation of CAE and Siamese in our case, we have proposed to extend CAE for novel supervised scenario by considering it as a one-class learning classifier in which a CAE is trained for each class and a Siamese is integrated as an alternative to the conventional loss of CAE. For each class, after training the CAE to reconstruct images from this class and to reconstruct images from other classes, Siamese is trained to distinguish the similarity and dissimilarity between the reconstructed leaf images from the trained class and the recon-structed images from the remaining classes. In contrast to the related hierarchical classification schemes, which require pre-knowledge of the dataset being recognized, our scheme consists of clustering the entire dataset to gather similar classes together. This strategy is simple, effective, and doesn’t require experts or botanists. The performance of our system has been evaluated on well-known leaf datasets, namely ImageCLEF2012, and the results demonstrate that our approach exceeds existing state-of-the-art methods. A hierarchical representation has reduced the complexity of the process of classification and reduced inter-species problems. Furthermore, our novel one class learning classifier has outperformed the results of our system and the proposed intelligent loss; Siamese has exceeded the results of the CAE. Our perspective in future work will be driven by exploiting more objects that present hierarchical organization, and we expect to get reliable results from this approach.

Chapter 9

9 Convolutional auto-encoder for plant diseases recognition

Contents

Convolutional auto-encoder for plant diseases recognition

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Abstract

Food security is one of the most important tasks that humans should take care of to protect their lives. Plant disease is one of the leading causes of food shortages, and therefore early detection of plant disease is highly needed to prevent them. However, manually detecting plant disease is considered a challenging task that requires special knowledge. Deep learning has recently been shown to be successful in a variety of disciplines. In this paper, we propose a convolutional autoencoder for feature extraction and a KNN for classification. The experiment was carried out using a dataset of 660 images. Promising results have been achieved.

Keywords: Food security, Plant leaves disease, classification, Auto encoder.

9.1 Introduction

The agricultural sector is one of the most important sectors that affect the international economy. Agriculture's effectiveness in any country is determined by the quality and quantity of agricultural goods produced. Algeria is regarded as one of the most agriculturally dependent countries in the world, with agricultural exports worth 12.27% [183].This agricultural richness must be maintained. Therefore, to increase the yield and develop agriculture products, caring and paying attention to the plants must be taken into consideration.

Plant diseases are one of the most serious issues that affect agricultural productivity, in the fact, plant disease not only damage the quality of fruits and vegetables, but they also frequently result in a considerable drop in worldwide crop production, posing a serious danger to global food security [176]. According to [184], the global population will rise by 2 to 4 billion people, increasing the need for food in the global market. Crop losses also have a substantial influence on farmers' financial losses, economic losses, and the ability of poor countries to get foreign currency. Plant diseases alone cost the world economy about US $220 billion per year in terms of economic value [185]. Early identification of plant diseases is critical for taking preventative actions and minimizing crop losses.

Symptoms of plant diseases [186] can be seen in several parts of a plant; nevertheless, leaves are the most commonly observed part for identifying an infection. Plant diseases that are caused by living organisms are known as biotic diseases. Different types of biotic diseases are caused by fungi, bacteria, and viruses. Abiotic, in contrast, are produced by non-living ecological circumstances such as hail, spring frosts, weather conditions, burning of chemicals, etc. Abiotics diseases are non-infectious, non-transmissible, and often preventable. Figure 9.1 depicts biotic and abiotic leaf disease.

Figure 9.1: Biotic leaf disease (a, d) and abiotic leaf disease (b, c).

Plant disease detection has traditionally been done visually by humans with training or experience detecting plant disorders using a variety of techniques such as molecular, serological, and Deoxyribose Nucleic Acid (DNA). Nonetheless, categorization by humans is subjective, necessitating a great deal of work from specialists, and it is both time and expense prohibitive. Automatically executing such a task using machine learning techniques, on the other hand, is quick, cheap, and accurate.

In the literature, many researchers have attempted to develop methods that can automatically detect plant disease. Some techniques have recommended handcrafted characteristics such as shape , texture, and color, or combinations of them [186]. Handcrafted characteristics are often defined manually and extracted using pre-programmed algorithms. However, this is a complicated procedure that necessitates modifications and recalculations for each problem or data set. With the advent of deep learning feature extraction, it has become possible to learn key features from raw images directly and automatically. Because of the high resemblance between some different diseases, performing quite representative features to precisely diagnose those diseases was of our interest. According to the literature, AE architecture has attracted numerous researchers to extract features or reduce dimensionality. In this paper, we present a CAE for feature extraction and a KNN for plant disease classification.

The evaluation of the proposed method is carried out on a dataset that contains 600 images, including 6 diseases of vegetable crops. The remainder of this paper is organized as follows. A brief review of related work is presented in Section 2. In Section 3, we describe the details of the proposed method. Experimental results are provided in Section 4. The final section presents our conclusions.

9.2 Related work

In recent years, a lot of efforts have been made to achieve more reliability in automatic plant disease detection. From the literature [187], two main approaches have been considered: hand-designed features and the deep learning strategy. As for the first one, features are selected manually and extracted through instructed algorithms, then only a subset of the most discriminant features are considered. For the second one, deep learning can automatically learn discriminative characteristics directly from raw images.

Several handcrafted methods have been proposed in the plant disease recognition domain. As instance, in [188] suggested an automatic method for detecting coffee plant diseases, based on the extraction of texture and color as exploited features and on ANN as a classifier. The system obtained 94.5 percent, it was tested on three classes. In [189] The authors provided an automated method for identifying and classifying leaf cucumber diseases. The suggested system is divided into three phases. The leaf images were separated from the compact region in the first stage using a super-pixel operation. The lesion is then obtained in the second stage based on the characteristics utilizing the frequency pyramid of histograms of orientation gradients (PHOG). The expectation maximization (EM) technique was used to segment the data. Support vector machines were employed to categorize the disease in the final stage. In [190] The authors present an automatic method for detecting and classifying leaf disease. For the feature extraction stage, two texture characteristics (GLCM and GWVT) have been extracted, and a KNN classifier for the classification stage. In [191] For the identification and recognition of diseases from paddy plant leaf pictures, two primary steps are used. Haar as a feature and Adaboost as a classifier are used to identify disease. In SIFT is used as a feature, and kNN and SVM are used as classifiers. However, applying identical weights to all features tends to minimize classification errors, which is why some authors take feature selection into account to improve the performance of their system. as instances [192] The authors created an automatic technique for detecting cucumber disease. Shape and color are retrieved characteristics from the affected region, and sparse representation methods are utilized to identify diseased leaf images. A system achieved an overall accuracy of 87.18 % on a dataset of seven cucumber leaf diseases. In [193] The authors propose an automatic system for identifying apple disease following lesion segmentation using EM. GA is used to optimize the extracted features, which include color, LBP, and color histogram. SVM is used to perform the classification. It should be noted that some works employ only one classifier in their systems. As a result, several additional studies have attempted to enhance them by integrating and employing many classifiers in their system. In [194] as instance, El Massi et al suggest using a hybrid combination of three classifiers. Their main idea was to select two SVM in serial combination and one SVM in parallel with them. Color, texture and shape features are extracted. The evaluation was performed on a dataset containing six disease classifications. The system produces good result. According to the literature, handcrafted features have been effective for several datasets; nevertheless, such extracted features are only reliable for a single dataset, and changing it requires recalculating the features. Furthermore, handcrafted features lack sufficient generalization power, especially when the number of classes is rather large. Deep learning has proven a huge success in numerous plant identification systems by automatically extracting characteristics in recent years to overcome the shortcomings of previously employed standard techniques. In [195] On the Plant Village dataset, authors compare the performance of six alternative fine-tuned CNN architectures: VGG16, Inception V4, ResNet with 50, 101, and 152 layers, and DenseNet with 121 layers. The DenseNet model appears to be the most effective. In [196] To classify tomato diseases of the PlantVillage Dataset, researchers employed the two well-known architectures, Alexnet and GoogleNet, with and without pretraining, and reached a top accuracy of 99.18 percent. Deep learning is used to solve a variety of image classification challenges. An auto-encoder is a neural network-based self-supervised learning approach. The goal of auto-encoding is to learn a mapping from high-dimensional observations to a lower-dimensional representation space such that the original observation may be approximated. It can be considered a useful technique for obtaining relevant features. As instance in [197] denoising convolutional variational autoencoders are proposed as a feature extraction method, with the output being fed into fully connected networks classifiers. The experiment is conducted out on the Plant Village dataset. Authors in [198] Pseudoinverse learning autoencoder using DCGAN is proposed to balance the dataset and extract significant features. Empirical results from the PlantVillage dataset have proved good result. In [199] The experiment is conducted out on two crops from the plantvillage dataset using an unsupervised convolutionnel auto encoder to extract relevant features and SVM for classification. Researchers have an open challenge in learning excellent features from data with minimal parameters. We propose in this paper to extract discriminative and representative features for classification using the AE and KNN.

9.3 Proposed method

This section provides details on the proposed method for the plant disease classification. We start by introducing the theoretical background of the CAE.

1. Theoretical background

Because we're dealing with images, a convolution layer is better for capturing spatial information. As a result, we employed CAE, which is often used, reducing reconstruction errors of image reconstruction is performed by learning the best filters.

A. Auto encoder:

An auto encoder (AE) [107] is an unsupervised neural network that uses machine learning. It consist of three layer (encoder, code and decoder) in the aim of the reconstruction of the input through a code. In the first layer encoder recieves an input $x \in X$ and maps it to the latent representation $X \rightarrow R$ (code second layer) in most cases, $r \in R$ is of a smaller dimension than x. This "code" is then used to reconstruct the input by a reverse mapping $R \rightarrow X$. The network is trained to find encoder and decoder functions such that minimize loss eg. $l\ (x;\ dec\ (enc\ (x)))$. In the literature, several kinds of auto encoders have been proposed. CAEs are similar to ordinary AEs, however the CAE differs in that the CAE's weights are shared across the inputs, retaining spatial locality, much like a CNN. Several filters with numerous parameters are employed to extract visual characteristics. CNN employs two different types of connections: convolutional and pooling.

- **Convolutional layer**

The convolutional layer is the central structural unit of a convolutional network and is responsible for the majority of computationally difficult tasks. This layer's attributes include a list of learnable channels. In the forward pass, we slide (or convolve) each channel along the width and height of the image's information volume and calculate the dot product of kernel and image pixels, while in the backward pass, we compute the gradients of loss with respect to weights, input, and bias. The following is a mathematical representation of a filter convolution over an image:

$$y_i^n = Relu\left(\sum_{m}^{M^{i-1}} W_{n,m}^i * x_m^i + b_n^i\right)$$

- **Max-Pooling Layer**

A pooling layer is added in the middle of many convolutional layers. It has the capacity to dynamically reduce the spatial size of the feature map. In order to reduce the number of parameters and computations in the system while also controlling overfitting. When the images get too large, we must minimize the number of trainable features, which is where pooling comes in. The most common types of pooling are maximal and average. Figure 9.2 depicts the architecture of the CAE (convolutional auto encoder).

The CAE's architecture is seen in the Figure 9.2 (convolutional auto encoder).

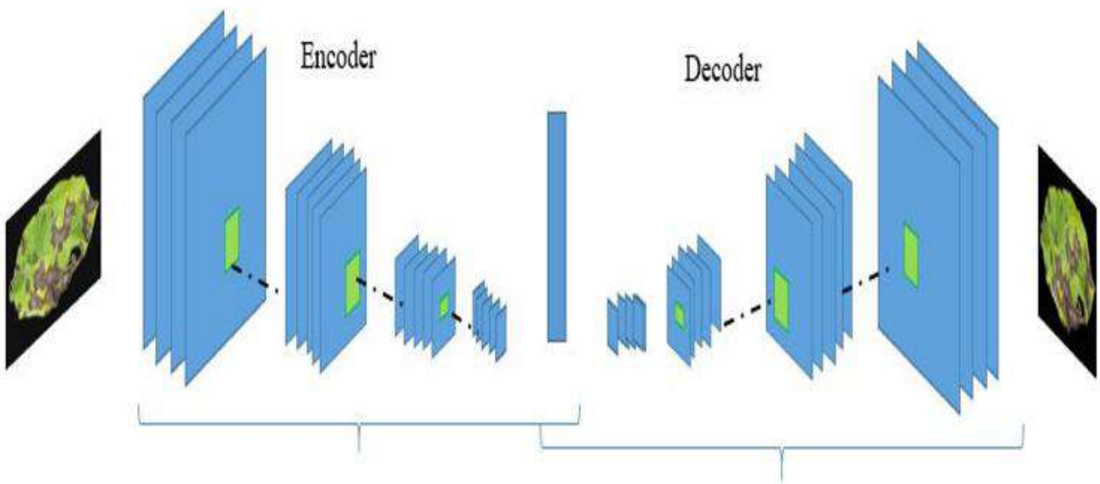

Figure 9.2 : CAE architecture.

2. Convolutional autoencoder neural network architecture

It consists of 3 convolutional blocks: Convolutional layer with 8 filters with 10*10, Relu activation function, and Max pooling layer, Convolutional layer with 16 filters with 5*5, Relu activation function, and Max pooling layer. Convolutional layer with 32 filters with 3*3, Relu activation function, and Max pooling layer and MSE is used as loss function.

B. Knn algorthim:

Knn [82]. This algorithm is used to categorize unknown samples based on their proximity to their neighbors. The nearest k training cases are used to classify an unknown disease. The sample's class is determined by the most prevalent class among these k neighbors.

9.4 Experimental results

Experiments were carried out on 284 images from the six classes chosen (48 Early blight, 41 Late blight, 46 Powdery mildew, 58 Leaf miners, 38 Thrips and 53 Tuta absoluta). In this experiment, the dataset is divided into two subsets: 202 images (70 %) for training and 82 photos (30 %) for testing. The dataset was gathered in the south of Morocco, with part of it coming through the internet. All of the images were cropped and the data augumentation technique was used before they were processed. The results show that this is mostly due to the tiny dataset and the success of the autoencoder release on a big dataset. Table 9.1 shows the acquired results.

Table 9.1: Results of CAE and KNN.

Approach	Result
CAE+KNN	33.82%

9.5 Conclusion

In this study, we suggest an automated plant disease system. Deep learning has yielded remarkable results in a wide range of applications. It has demonstrated its value by automatically and directly extracting attributes from raw images. The AE is a well-known deep learning architecture that has attracted the attention of many researchers because of its ability to decrease dimensions and extract features. Our method has demonstrated that the autoencoder's superiority and efficacy are dependent on large datasets with just a few number of images a low result has been achieved.

Chapter 10

10 General Conclusion

10.1 Conclusion

In light of the importance of agriculture as a sector for human life, whether in terms of the environment (Oxygen, clean air, and water) or the economy (medicine, food and so on), human have paid a serious attention on it. Plants are an important object in the agricultural sector. Classifying plant species and establishing them before they become extinct is highly needed, but establishing them is not the only danger that menace agriculture sector, plant are threatened by several disease an early detection is vital for the prosperity of agriculture productivity. Manual plant species or disease identification are extremely difficult procedures that typically take time and need the presence of an expert, who is not always present. In our thesis, we primarily addressed two agricultural problems: plant species identification and plant disease detection based on a leaf.

Several contributions have been proposed to deal with the first probelm in the **Chapter 2** in the purpose of establishing the automatic plant systems that has been proposed we have presented a state-of-the-art of several methods ranging from feature extraction with its different categories (generic, specific) features. Several classifiers and deep learning architectures has been presented, and the most well-known dataset that has been exploited in different reasercher are mentioned, at the end the limmitations of the related work are noted.

In **Chapter 3,** because the leaf is characterized by shape and veins, we have proposed designing a fully automatic method for plant identification based on shape features and texture features. Experimental evaluation shows that our method yields good results, which includes that our proposition is right and (shape with veins) represents a relevant feature for distinguishing leaves. Although the advantages of this solution consist of being simple and rapid, however, it is not always sufficient to provide accurate identifications, mainly due to the "semantic gap" between such representations and high-level semantics (intra and inter-species problems). Presenting a specific feature that is designed for leaf is a solution for "gap semantic". Leaf shape contours contain many relevant characteristics that distinguish between species, such as base, apex, and center. In **Chapter** 4, we have mainly focused on the extraction of shape features from only these discriminative parts. Results have proven that the proposed feature can reduce the problem of inter and intra-species with good results, but classifying plants based on their shape alone is not sufficient to identify plants.

Regarding the literature, several classifiers have been proposed to solve problems, and it is mentioned that the outcome of such classifier combinations can be superior to all the individual classifiers. In order to improve the accuracy of plant identification systems, In **Chapter 5,** we have proposed dealing with two parallel combination methods. By extracting morphological features from plant leaf images and by using the "**Majority Vote**" combination method, the results have not improved against the individual classifier. The second combination method, "**Weighted Majority Vote,**" by considering the weight for each classifier, indicates a significant improvement regarding individual classifiers and the majority vote method, which thus includes that the pre-knowledge of the classifier performance is very important before combination schemes.

By considering the pre-knowledge of classifiers' performances in **Chapter 6,** we have dealt with serial combinations based on revaluation techniques of two classifiers. We have concluded that results can be improved and are much better than a single classifier, but this technique is very challenging and it is sensitive to the first classifier.

With the aim of comparaison of several parallel combination methods in **Chapter 7**, our findings show that the Nave Bayes NB combination technique has yielded the best results. This could be attributed to its parametric priorities that utilize big base validation; the Min method has performed the worst because of its sensitivity to the erroneous decision produced by any classifier in the combination.

From the literature, deep learning algorithms have proved their effectiveness against hand-crafted features by the automatization feature extraction process. However, they have several properties that can be considered to improve and give reliable results. In **Chapter 8,** Rather than the conventional exploitation of CAE and Siamese, in our case, we proposed CAE as a new classifier. And contrary to the state of the art, we propose a one-class hierarchical classification scheme that does not require such prior knowledge and can be used even by non-specialists automatically, such that we group the dataset to assemble similar classes. A test image is first assigned to the closest cluster and then matched to a class among the classes that fall under the determined cluster using our new one-class classifier. The proposed method was evaluated on a known dataset, ImageCLEF2012. Results show that proposing a one-class learning classifier and a hierarchical strategy are very effective for reducing the intra and inter-species problems. The experimental results proved the superiority of our method compared to several other methods.

Lack of agricultural products presents a critical and challenging task such as food security and many others. The diminution of yields may cause a very serious loss to a farmer in particular and to the national economy in general. Plant disease presents one of the main major problems that menace humanity, so paying attention to it to save humanity is highly needed. In **Chapter 9,** we dealt with such a critical problem. Since the AE has proved its effectiveness in several fields, such as feature extraction and dimensionality reduction, in this chapter, we have proposed an automatic system based on AE for feature extraction and KNN for classification. Results indicate that the AE is very swetible for the representation of leaves in an automatically generated way and directly from images.

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10.2 Future Work

From our reaserch, we propose to improve our systems by:

- Multimodal for plant species by the combination of another organ rather than leaf alone allows taking advantage of the data complementarity and therefore potentially to have higher performances than those obtained when using a single organ.
- Intra variability of species where leaves from the same species may variate according to the age or to the season, it would be better to take into consideration information about the main features of these changes that may to each species and develop an interactive system to consider this information about season and age of the plant.
- Plant diseases are presented with only some examples to overcome this problem, it would be interesting to consider one-shot learning strategies.
- Tested the system with other objects to render it a generic system.
- Establishing dataset for Algeria plants.

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