PEOPLE'S DEMOCRATIC REPUBLIC OF ALGERIA
Ministry of Higher Education and Scientific Research
University of KASDI MERBAH OUARGLA
Faculty of New Technologies of Information and Communication
Department of Electronic and Telecommunications

ACADEMIC MASTER'S DISSERTATION

in : Electronic

Specialty : Electronic of Embedded Systems

By: Benattous Houssem Eddine
Brakta Yahia
Beggari Abdellatif

Theme

Date Fruit classification using Convolutional Neural Network Models

Publically presented in the 19th June 2024

Before jury :

Dr. D. Belkbir	MCB	Ouargla University	President
Prf. F. Chrif	PRF	Ouargla University	Supervisor
Dr. K. Maarouf	MCB	Ouargla University	Examiner

ACADIMEC YEAR : 2023/2024

بسم الله الرحمن الرحيم

رَبِّ زِدْنِي عِلْمًا

صدق الله العظيم

Dedication

First of all, I dedicate this work to my dear parents. My father **Muhammed**, and my mother **Djamila** , for their support of me and providing me with all the conditions for studying. They are the main reason after God for my reaching this stage of study. I also want to thank my older sister **Nadira**, my sister **Majda** the second mother. My brother **Mustafa** is the main reason for my choice This field, my brother **Tarek** I will not forget your grace when I reached this stage that you were keen on my studies when I was young, and my sister **Dalia** for supporting me at all times. I also want to thank the grandchildren, **Amani**, **Nour** ,**Abdelkader**, **Mariam** ,**Asma** ,**Salma** , **Khayer ElDinne** and **Rami** .and all my family for their Unwavering support.

Finally, I would like to thank all my colleagues for their valuable Contributions and support.

Benattous Houssem Eddine

Dedication

First of all, I dedicate this work to my dear parents, my father **Hacene** and my mother **Amel** who were everything to me, Their unwavering love and support have been a constant source of motivation throughout my academic journey. Their patience and encouragement have been helpful in my success, and I am forever grateful for Their sincere and deep love. I would also like to express my appreciation to my brother: **Youcef Khaled**, my sisters **Douaa and Ghoufrane**, and all my family for their unwavering support.

Finally, I would like to thank all my colleagues for their valuable contributions and support.

Brakta Yahia

Dedication

First of all, I dedicate this work to my dear parents, my father **Mohamed** and my mother **Ouarda** who was everything to me, her unwavering love and support have been a constant source of motivation throughout my academic journey. Her patience and encouragement have been helpful in my success, and I am forever grateful for her sincere and deep love. I would also like to express my appreciation to my brother: **Mouatez**, my sisters **Mouna, Khaouther, Maria** and all my family for their unwavering support.
Finally, I would like to thank all my colleagues for their valuable contributions and support.

Abdellatif Beggari

Acknowledgement

First of all, I thank ALLAH from the bottom of my heart for having enlightened me on the right path.

I would like to extend my heartfelt appreciation to my family for their unwavering support and sacrifices. Words cannot express my gratitude to our supervisor, ***Prf. CHerif folla*** *, for his constant availability, patience, and guida us throughout this work. His invaluable contributions have been instrumental in our success. I also extend my sincere thanks to the members of the Jury for accepting the responsibility of evaluating our work :*

Dr. Belkbir Djalila *President.*

Dr. Maarouf Korichi *Examiner.*

I am also grateful to all the teachers who have imparted their knowledge and provided encouragement on our journey.

﴿ وَهُوَ الَّذِي أَنزَلَ مِنَ السَّمَاءِ مَاءً
فَأَخْرَجْنَا بِهِ نَبَاتَ كُلِّ شَيْءٍ فَأَخْرَجْنَا مِنْهُ
خَضِرًا نُّخْرِجُ مِنْهُ حَبًّا مُّتَرَاكِبًا وَمِنَ
النَّخْلِ مِن طَلْعِهَا قِنْوَانٌ دَانِيَةٌ وَجَنَّاتٍ مِّنْ
أَعْنَابٍ وَالزَّيْتُونَ وَالرُّمَّانَ مُشْتَبِهًا وَغَيْرَ
مُتَشَابِهٍ ۗ انظُرُوا إِلَىٰ ثَمَرِهِ إِذَا أَثْمَرَ وَيَنْعِهِ ۚ
إِنَّ فِي ذَٰلِكُمْ لَآيَاتٍ لِّقَوْمٍ يُؤْمِنُونَ﴾

ملخص

يعد إنتاج ثمار التمر جزءا مهما من القطاع الزراعي في الجزائر ، والمعروف بزراعة أنواع نخيل التمر المتنوعة. تقدم هذه الدراسة طريقة جديدة لتصنيف ثمار التمر تعتمد على تقنيات التعلم العميق ومصممة خصيصا للاستخدام في الجزائر مع إطار كيراس. أولا، نحن نقدم لمحة عامة عن مجموعة واسعة من أصناف نخيل التمر الجزائري، التي لها سمات مورفولوجية وكيميائية حيوية مميزة. ثم ننتقل إلى التحقيق في التحديات المرتبطة بالتصنيف الدقيق ، بما في ذلك اللون والشكل والحجم والنضج. نقدم نموذج الشبكات العصبية التلافيفية الذي يعتمد على كيراس ويلتقط جميع الميزات الحيوية لصور البيانات. نحن نعتبر إنشاء مجموعة بيانات للتدريب والتحقق من الصحة لأنها مهمة جدا لدقة نموذجنا. من أجل تحليل مهمة التصنيف ، نستخدم الخوارزمية القائمة على الشبكات العصبية التلافيفية بحساب الدقة والاستدعاء ومقاييس نقاط ف١ لإظهار مدى جودة أداء شبكاتنا العصبية التلافيفية في مثل هذه الإعدادات. في الوقت نفسه ، نتحدث عن فائدته عند استخدامه في المجال الزراعي الجزائري ، أي كيف يمكنه تبسيط عمليات مراقبة الجودة لبعض السلع الأخرى ، أو توفير خيارات أفضل لإدارة الموارد ، أو تعزيز المنافسة في السوق. بشكل عام ، تبين أن طرق التعلم العميق ، بما في ذلك الشبكات العصبية التلافيفية باستخدام كيراس ، قادرة على التغلب على هذه التحديات في السياق الزراعي الجزائري. من خلال تبني الحلول التكنولوجية المبتكرة ، يمكن للجزائر تسخير قوة الذكاء الاصطناعي لدفع صناعة التمور نحو مزيد من الكفاءة والإنتاجية والاستدامة.

الكلمات المفتاحية: تصنيف؛ فاكهة التمر ؛ تعلم عميق؛ الشبكات العصبية التلافيفية؛ الذكاء الاصطناعي؛ كيراس.

Abstract

The production of date fruits is an important part of Algeria's agricultural sector, known for its cultivation of diverse date palm species. This study introduces a new method for date fruit classification based on deep learning techniques and designed specifically for use in Algeria with the Keras framework. First, we provide an overview of the wide variety of Algerian date palm cultivars, which have distinct morphological and biochemical features. Then we proceed to investigate challenges associated with precise classification, including color, shape, size, and ripeness.We present the CNN model that is based on Keras and captures all vital features of the data images, which are date fruit. We consider constructing a dataset for training and validation as it is very important for the accuracy of our model. In order to analyze the classification task, we use the CNN-based algorithm with accuracy, precision, recall, and F1-score metrics to show how well our CNN performs in such a setting. At the same time, we talk about its usefulness when being used in the Algerian agriculture sphere, namely how it can streamline quality control processes for some other commodities, provide better resource management options, or promote competition in the market. Overall, deep learning methods, including CNN using Keras, are shown to be able to overcome these challenges within the Algerian agricultural context.By embracing innovative technological solutions, Algeria can harness the power of artificial mtelligence to propel its date industry towards greater efficiency, productivity, and sustainabiliry.

Keywords: classification; date fruit; deep learning; convolutional neural networks; artificial intelligence; Keras.

Contents

List of Figures

List of Tables

Acronyms

AI Artificial intelligence.

ANN Artificial Neural Network.

AUC Area-under-curve.

CNN Convolutional Neural Network.

Conv Convolution.

CV Computer Vision.

DL Deep Learning.

FC Fully-Connected.

FN False Negative.

FP False Positive.

ML Machine Learning.

OS Operating System.

ResNet Residual Network.

TP True Positive.

General Introduction

Dates fruits are an excellent source of carbohydrates, essential vitamins, fibers, and minerals. They contribute significantly to human health by providing strength and aiding in the treatment of ailments such as stomach upsets and memory disorders. Oman holds the 9th position in global dates production, with dates comprising 80% of its fruit crop yield. Of the dates produced, approximately 50% are consumed by humans, while the remainder is used as animal feed or goes to waste. Although dates are Oman's most notable export, they represent just 2.6% of total production. This low export rate is partly attributed to inadequate post-harvest handling, resulting in lower prices for Omani dates in international markets compared to those from other countries.

Optimizing the profitability of date palms is crucial, as it directly impacts the lives of Omani citizens. Effective post-harvest processing systems are vital for improving recovery rates and boosting market and export potential. The variety of dates grown in Oman differ in shape, size, texture, color, hardness, and taste, influencing their market value. Traditional classification relies on human visual inspection, which is time-consuming and inconsistent due to variability in human judgment and mood. Therefore, advanced processing and handling systems are essential for enhancing national income and GDP.

Quality grading systems for dates are categorized by internal and external factors. External factors include visual attributes like color, shape, and size, while internal factors encompass sweetness, aroma, flavor, and taste. Some qualities, such as toughness, crispness, and firmness, straddle both categories. Internal quality-based grading can be destructive or non-destructive; the latter employs spectroscopic and hyperspectral imaging techniques, preserving the fruit's quality during grading.

Currently, external quality-based grading systems are favored for their simplicity and practicality. Innovations in image processing and machine learning offer robust solutions for automatic fruit classification. A comprehensive literature review indicates significant research and advancements in these technologies, leading to more efficient and accurate fruit grading methods. Our study aims to categorize dates fruits based on their physical attributes like shape and color using deep learning model(CNN). [8]

We have chosen to focus our study on four main chapters:

Chapter I : Provides a comprehensive overview of the date palm Especially about date fruits including definitions, and terminology that are essential for understanding this field. The chapter also covers Types of date fruit and their characteristics . Additionally, Learn about some common databases in the field of in the classification of date fruit that will be used in our study, the chapter addresses the most productive countries in the world and the healthy benefits of date fruits.

Chapter II : Explain the difference between machine learning and deep learning. the chapter also introduced the Artificial Neural Networks (ANN),and then talking in details about Convolutional Neural Networks (CNN) and their structures. Additionally, paying attention to the study focus which is the "MobileNet" architecture. Finally the chapter discuss the architecture of each MobileNet type in details.

Chapter 1

Introduction to date fruit classification .

1.1 Introduction

In this chapter, we will give generalities about date palms and date fruits, where they are found, the most productive countries and the most famous varieties of them as well as the characteristics of each species , Then we know about its health benefits. We will also get acquainted with the databases used in this study .

1.2 The date palm

The date palm is one of the earliest cultivated fruit trees in the world. It is one of the classic fruits of the Old World, alongside olives and figs [9].It is mainly grown in well-drained sandy soils and regions that are both, dry, and low in humidity [1].

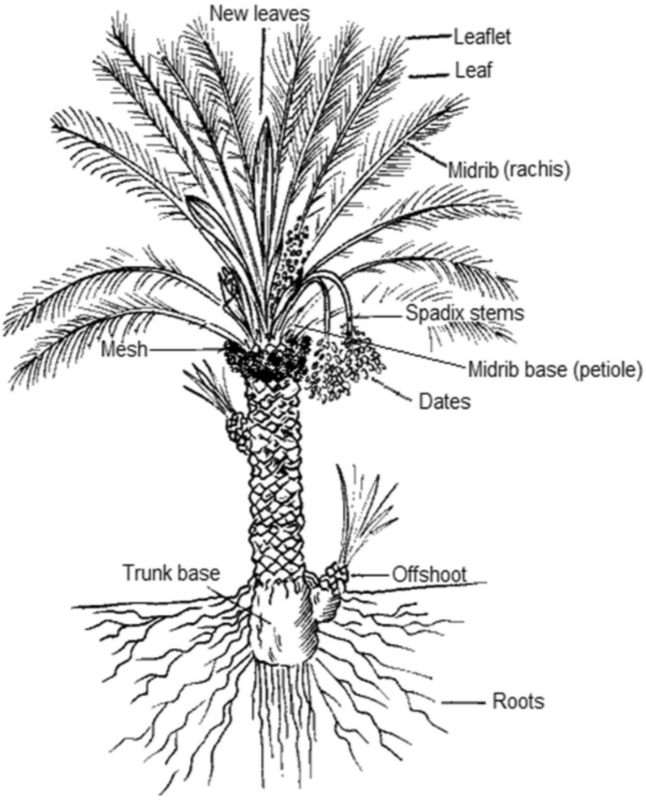


Figure 1.1: Palm and its components [1]

A diploid (2n = 2x = 36), perennial plant in Palmaceae (Barrow, 1998) is date palm. Its name derives from the fruit: "phoenix" comes from Greek and signifies purple or red (fruit), while "dactylifera" alludes to the finger-like cluster shape due to its appearance. it is dioecious , having distinct female and male trees [2].

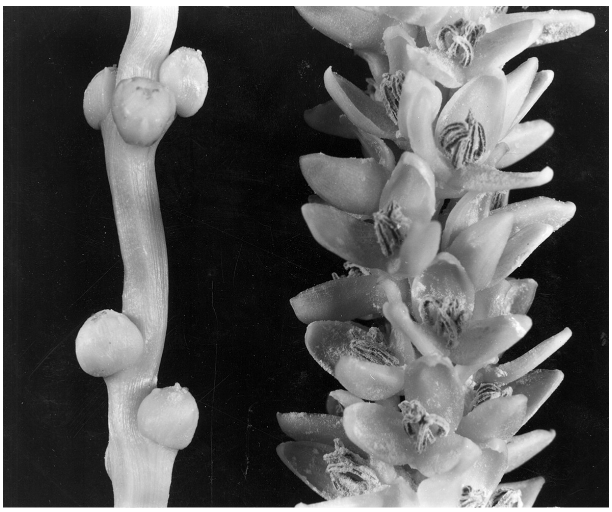


Figure 1.2: flowers of date palm (male in the left and female in the right) [2]

Life cycle and cultivation of date palm trees [10]:

The date palm tree has a complex life cycle. It begins with germination and the seedling stage where seeds are planted in soil that drains well after being soaked in water. When the seedlings have matured they are transplanted into the field during the period when regular watering is done from the nursery bed to their planting point. During vegetative growth which involves formation of trunk and leaf crown, date palms require regular watering and application of fertilizers to supplement the nutrient deficiency [1]. Male and female plants begin to be distinguished after four to eight years when sexual organs start to appear; pollen-producing males and fruit-bearing females are identified based on this differentiation [2]. Fruit development depends upon wind-assisted pollination, so it is essential that male trees producing pollen are close enough to reach female fruit clusters through wind transfer. For successful fruitioning stage: proper irrigation should be ensured throughout development which takes months before harvesting, also protection from pests during floral emergence as well as diseases up to maturity is necessary [11]. Seeds extracted from mature dates are the typical way date palms are propagated. These seeds are soaked before planting in soil that drains well, which is how germination is initiated. When the seedlings emerge after germination, they are taken to the field. However, propagation can also be done using offshoots or suckers from mature trees—this way provides a means for clonal propagation. It takes 4–8 years to identify male and female plants that guide planting arrangements for wind-assisted [12], pollination with date palms achieving full production typically between 15 and 20 years old although they start bearing viable fruit around 6–10 years. Date palms have quite a reputation when it comes to longevity as their lifespan spans several decades; some even make it past the century mark [2].

Figure 1.3: Life cycle and cultivation of date palm trees

1.3 Date fruit

1.3.1 Date fruit Definition

Dates are fruits that are derived from a species of flowering plants in the family of the palm, known as Phoenix dactylifera, or date trees. The trees are dioecious, which means that each plant is either male or female, but only the female plant is capable of producing fruit. It all begins with the planting of a seedling or offshoot that is carefully cultivated for seven years before being fertilized. [13]

Date fruits (dates) are spherical, 3 to 7 centimeters (1 to 3 inches) long, and have a diameter of about 2.5 centimeters (1 in). Their color is dependent on the variety, it can be dark brown, or bright red or yellow. Containing between 61 and 68 percent sugar by mass when stored. [14]

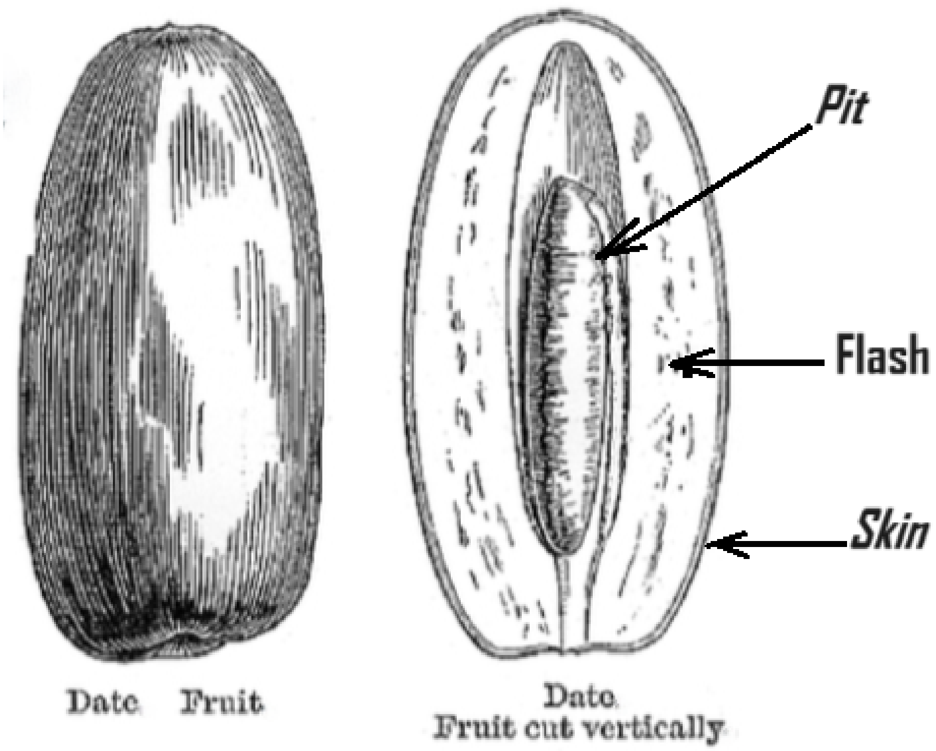


Figure 1.4: Date fruit and its ingredients

1.3.2 Stages in the development of the date fruit

The development of the fruit is classified into four stages [15]:

The first stage is the 'Kimri' stage :

It consists of two phases. In the first phase, a date can be identified by its rapid growth in size and weight. - High acidity and high moisture content contribute to the rapid accumulation of sugars. Two things are noticeable during the second phase: growth continues but at a slower pace than before and so does the increase in weight. Reduced rate of sugar accumulation at a lower level and slightly reduced acidity. . Average, a larger quantity of moisture is present than that in the first stage. During the Kimri stage, the average fruit length is 27.5 mm while its diameter stands at 17.8 mm.

Figure 1.5: kimri stage [3]

Stage 2 'Khalal' stage :

The color of the date changes from green to somewhere in between yellow and red (3-5 weeks). The rate at which the four characteristics evolve during phase two. The average fruit length increases to 32.5 mm in this stage and the diameter also increases to 21 mm.

Figure 1.6: khalal stage [3]

Stage 3 'Rutab' stage :

During the third stage, known as the "Rutab" stage, the date starts to undergo a softening process and gradually loses moisture content. weeks). During this stage, the percentages of protein, fat, and ash decrease to 2.6%, 0.3%, and 2.6% respectively.

Figure 1.7: Rutab stage [3]

Stage 4 'Tamur' stage :

The dates are now quite firmly dried. Consistent with darker colors, but with Do not develop into such a data type stage.

Figure 1.8: Tamer stage [3]

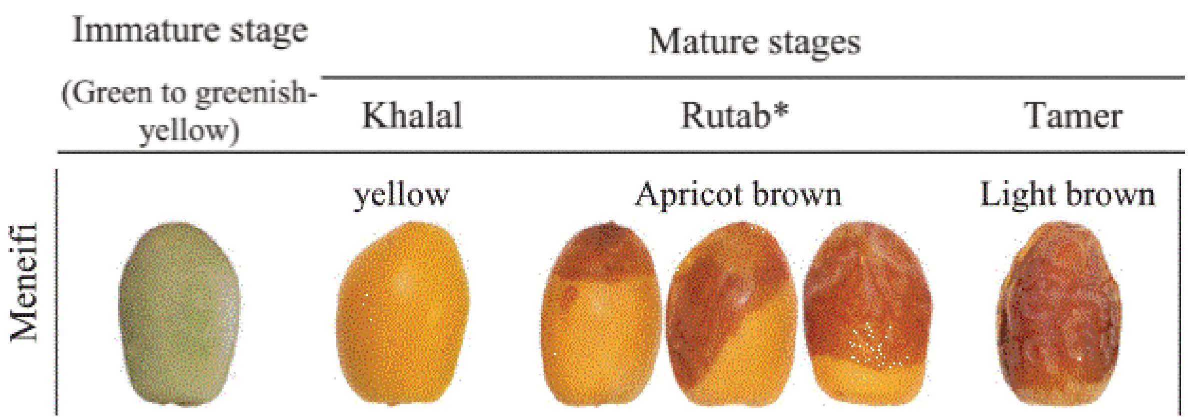


Figure 1.9: Ripening stages of Meneifi date fruit [4]

Samples of the identical variety are also possibly different to a great extent in relation to their level of maturity, degree of hardness, and shape . [5].

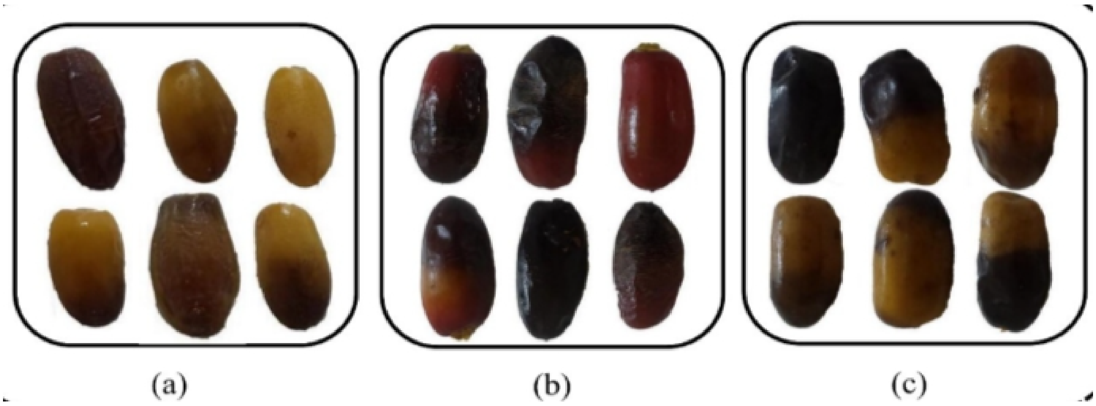


Figure 1.10: Typical varieties with a large intra-variation.(a) Bad mama (b) Namrata (c) Finishing [5].

1.3.3 Types of date fruit and their characteristics

Date fruits take various forms in many countries worldwide. Each type is unique based on taste, texture, color, and size (all factors). It's impossible to count them due to the different cultivation methods and people's regional preferences but there are more than one hundred types of dates around the world. Some well-known varieties are Medjool, Deglet Noor, Zahidi, Barhi, Halfway and Khadrawy...; each type has specific growing requirements and is preferred for different uses either in cooking or consumption.

The most popular types of date fruits :

Date Type	**Characteristics**	**Whereabouts**
Ajwa 	Tiny and dark brown, with tenderness in texture, sweetness in taste. Acclaimed for It has medicinal properties and is often used in traditional remedies.	The date palm trees are grown primarily in the region of Madinah, Saudi Arabia.
Galaxy 	Medium in size, reddish brown to dark brown, soft in texture with a flavor resembling that of caramel is known and relished by many for its unique taste and consistency.	It is grown in different areas including California, USA, and some Middle Eastern countries such as Iran and Saudi Arabia.

Mejool 	A large-sized, dark brown to amber in color, soft and moist with a rich caramel-like flavor— this date is regarded as one of the best varieties available	Its origins lie in Morocco but it has found new homes in regions like California, USA and certain Middle Eastern countries such as Jordan.
Meneifi 	Medium-sized and colored light brown to golden, it is firm yet chewy with a mild sweetness. Commonly an ingredient in date-based desserts and snacks.	primarily cultivated in Egypt, notably within the Nile Delta area.
Nabtat Ali 	Rich in nutritional value and popular because of its quality, it has sweet notes with a hint of nuttiness. The fruit is small to medium-sized, dark brown in color; the texture is soft and juicy.	Cultivated predominantly in the United Arab Emirates, with focus on Al Ain area.
Rutab 	Fresh dates, harvested in the "rutab" stage, are characterized by a soft, moist texture and a sweet, honey-like taste. Usually eaten fresh rather than dried.	Found in different date-growing regions around the world, including the Middle East, North Africa, and parts of Asia.
Shaishe 	Medium in size, reddish brown to dark brown, firm and chewy, sweet and slightly spicy. Often used in date candies and desserts.	Commonly cultivated in Iraq, especially in the Basra and Qadisiya areas.

Sokari 	Small to medium-sized, dark brown to black in color, soft and tender with a rich, molasses-like flavor. Often used in traditional Arabic cuisine and desserts.	Mainly cultivated in Iraq, particularly in the southern regions like Basra and Wasit.
Sugaey 	Medium in size, light brown to golden, firm and chewy with a sweet caramel-like flavor. Known for its high sugar content and long shelf life.	Mainly found in Oman, especially in the Jebel Akhdar mountains.

Table 1.1: Types of date fruit and their characteristics

1.4 Health benefits of dates

Dates have a rich nutritional profile.since they're dried, their nutritional value is higher than the majority of fresh fruit. The calorie content of dates is comparable to that of other dried fruits, such as raisins and figs. [16]

As an example: A 3.5-ounce (100-gram) serving of Medjool dates provides the following nutrients [16]:

Nutrient	Amount
Calories	277
Carbs	75 grams
Fiber	7 grams
Protein	2 grams
Potassium	15% DV
Magnesium	13% DV
Copper	40% DV
Manganese	13% DV
Iron	5% DV
Vitamin B6	15% DV

Table 1.2: Nutritional Information for Date Fruit(Medjool dates)

Vitamin:

Dates contain more than six vitamins, including : Vitaminc-Folacin-B2 - B1-A ... [15]

Antioxidants:

Also, dates have a high concentration of antioxidants, which may contribute to their numerous health benefits [17].The function of antioxidants is to shield your cells from free radicals, which are unstable molecules that have the potential to trigger harmful reactions in your body and contribute to the development of diseases [18].

fiber:

Dates contain enough fiber to benefit human health.A high fiber diet can benefit digestive health by preventing constipation as it promotes regular bowel movements which helps to form stool [19].

Some studies have also confirmed that eating dates greatly benefits pregnant women because it contains compounds that help them do this. Tannins are found in dates and have been demonstrated to assist in facilitating contractions because of their properties. Moreover, dates are a good source of natural sugar as well as calories— both essential for sustaining energy levels while in labor [20].

Date fruits are rich sources of organic and medicinal diets, usable for a variety of by-products regardless of their monetary worth.

1.5 The most date fruit producing countries in the world:

The production and consumption of dates are primarily concentrated in Middle Eastern and North African nations. The cultivation of dates is intricately tied to the land and water footprints, which poses a significant issue for countries where arable land and fresh water resources are limited [21].

The following table shows the countries producing dates and the amount of production in 2021, as well as the types of dates in each country:

Country	Production (Metric Tons) [22]	Types of Dates [23]
Egypt	1.7 thousand million kilograms	Hyani and Zaghloul
Saudi Arabia	1.6 thousand million kilograms	Khalasah, Ajwah, Al Khunaizi,Medjool, and Rtab
Iran	1.3 thousand million kilograms	Mazafati, Zahedi,Rabbi and Kabkab
Algeria	1.2 thousand million kilograms	Deglet Noor,Tgoory and Lteema
Iraq	0.8 thousand million kilograms	Amir Haji, Dayri and Khstawi
Pakistan	0.5 thousand million kilograms	Aseel, Zahidi, Fasli, Maazwati, Dhakki, Kharbalian and Begum Jangi
Sudan	0.5 thousand million kilograms	Bireir, Abid Rahman and Barkawi

Table 1.3: The most date fruit producing countries in the world (in 2021)

1.6 Data Collection

Dataset-9 of Esraa.A.Abdelrazek

Dataset-9 was created by ESRAA.A.ABDEL RAZEK, the images in this dataset are collected from Kaggle (classification of dates by Esraa.Abdelrazek). This dataset contained 9 date varieties (Ajwa(140), Galaxy(152), Medjool(108), Benefit(185), Habitat All(141), Rutab(116), Shaikh(136), Sokari(211), Sugaey(134)). These pictures were taken in high quality with a white background for a good lighting with many gestures.

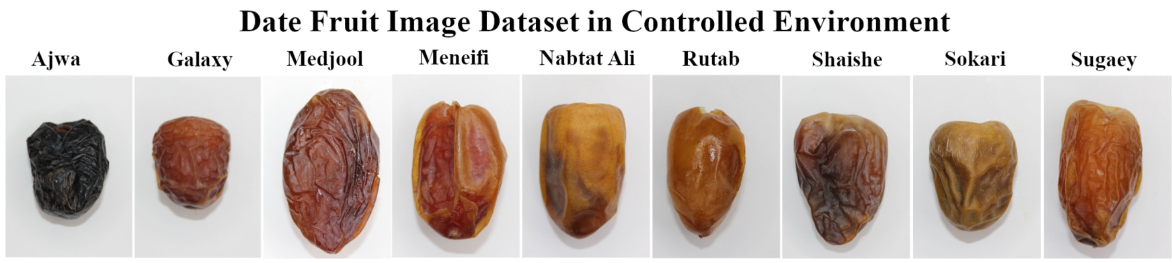


Figure 1.11: Types of dataset-9 used [6]

Dataset-20 (2022)

Dataset-20 was created by Oussama Ayadi and others , the images in this dataset are collected from article (classification of dates by Oussama Ayadi and others). This dataset contained 20 dates varieties(Ajina(85), Adam Deglet Nour(86), Ghars(88), Litima(85), Bayd Hmam(87), Deglet Kahla(85), Bouaarous(82), Degla Bayda(95), Deglet Ghabia(35), Dfar Lgat(86), Dgoul(103), Tarmount(83), Tanslit(85), Deglet(38), Tantbucht(76), Techbeh Tati(88), Tivisyaouin(87), Tinisin(88), Loullou(81), Hamraya(76)). These pictures were taken in high quality with a white background for a good lighting with many gestures.

Figure 1.12: Types of dataset-20 used [7]

Table 1.4: The data set used

Database	Images	Year	Varieties
Dataset-9	1323	2021	9 Varieties
Dataset-20	1619(The image used are 1133)	2022	20 Varieties(The varieties used are 13)

1.7 Conclusion

In this chapter, we presented the conceptual framework of our thesis, which included the main definitions and principles related to date palm and the date fruits and its various types. We discussed the most important characteristics of different species, and where they are located . Also We explored the health benefits of dates , highlighted the most productive countries .
In addition, we have summarized the existing databases available for classifying types of dates .

Chapter 2

Overview of Artificial Intelligence and Neural Networks

2.1 Introduction

In this chapter, we will talk about convolutional neural networks, the most popular types of neural networks, exploring their structure and prominent models, as we prepare to utilize them in our research. Our primary focus will be on Mobilenet V2, a specific type of convolutional neural network, and how to leverage them effectively for enhanced accuracy.

Learning objectives:

- We will learn some different types of neural networks (others include recurrent neural networks (RNN), artificial neural networks (ANN), and convolution neural networks (CNN)).

- We will learn how CNNs work for the image classification task and how the CNN model for image classification is applied.

- We will cover the fundamentals of machine learning and deep learning, highlighting their most significant types and applications.

2.2 Artificial intelligence

Artificial intelligence (AI) refers to the intelligence demonstrated by machines. In computer science, AI research is defined as the study of "intelligent agents," which are devices that perceive their environment and take actions to maximize their chances of achieving specific goals. Commonly, the term "artificial intelligence" is used when a machine mimics cognitive functions associated with the human mind, such as learning and problem-solving.

AI capabilities currently include understanding human speech, competing at a high level in strategic games like chess and Go, operating self-driving cars, intelligent routing in content delivery networks, military simulations, and interpreting complex data.

The primary goals of AI research encompass reasoning, knowledge, planning, learning, natural language processing (communication), perception, and the ability to move and manipulate objects. One of the long-term objectives in the field is achieving general intelligence. Approaches to AI include statistical methods, computational intelligence, and traditional symbolic AI. Various tools are utilized in AI, including search algorithms, mathematical optimization, logic, and methods based on probability and economics. The field of AI draws from several disciplines, including computer science, mathematics, psychology, linguistics, philosophy, neuroscience, and artificial psychology, among others. [24]

2.3 Deep Learning and Machine Learning

Deep learning is a subset of machine learning methods focused on learning data representations. An observation, such as an image, can be represented in various forms, such as a vector of pixel intensity values or more abstractly as a set of edges or specific shapes. Certain representations are more effective at simplifying learning tasks, such as face recognition or facial expression recognition [25]. One of the key advantages of deep learning is its ability to replace handcrafted features with efficient algorithms for unsupervised or semi-supervised feature learning and hierarchical feature extraction [26].

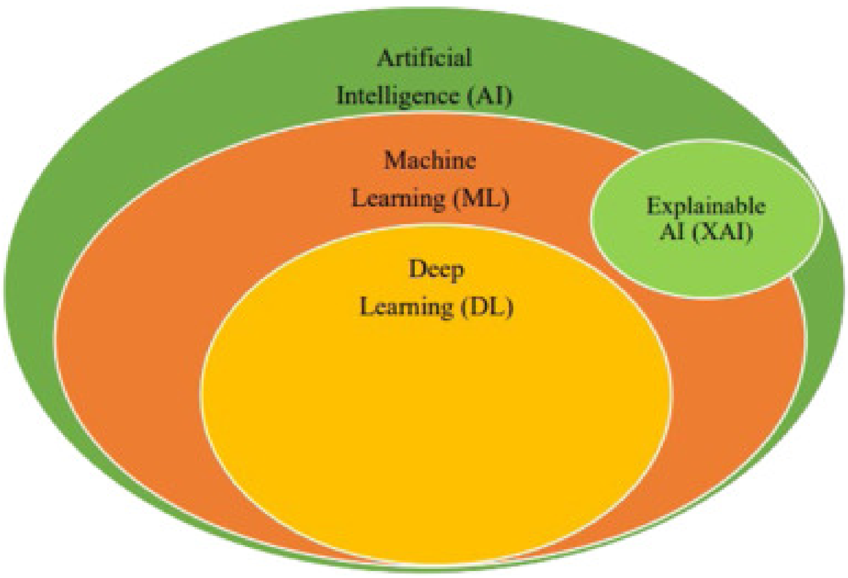


Figure 2.1: Shows the correlation between artificial intelligence (AL), machine learning (ML), and deep learning (DL). [27]

2.4 Artificial Neural Network (ANN)

Artificial Neural Networks (ANNs) are essentially highly parallel computational models designed to mimic the function of the human brain. An ANN consists of numerous simple processors interconnected by weighted connections. These processing nodes, analogous to neurons, rely only on the local information available at the node, either internally stored or received through the weighted connections. Each node receives inputs from multiple other nodes and transmits its output to additional nodes. Individually, a single processing element is not very powerful; it generates a scalar output, which is a simple non-linear function of its inputs.

In ANNs, the designer selects the network topology, the performance function, the learning rule, and the criteria for stopping the training phase, while the system automatically adjusts the parameters. This makes it challenging to incorporate prior information into the design and difficult to incrementally refine the solution when the system does not perform correctly. However, ANN-based solutions are highly efficient regarding development time and resources, and for many complex problems, ANNs deliver performance that is hard to match with other technologies. Denker, a decade ago, stated that "artificial neural networks are the second best way to implement a solution," highlighting their simplicity and universality, second only to traditional designs based on studying the problem's physics. Currently, ANNs are becoming the preferred technology for numerous applications, including pattern recognition, prediction, system identification, and control. [28]

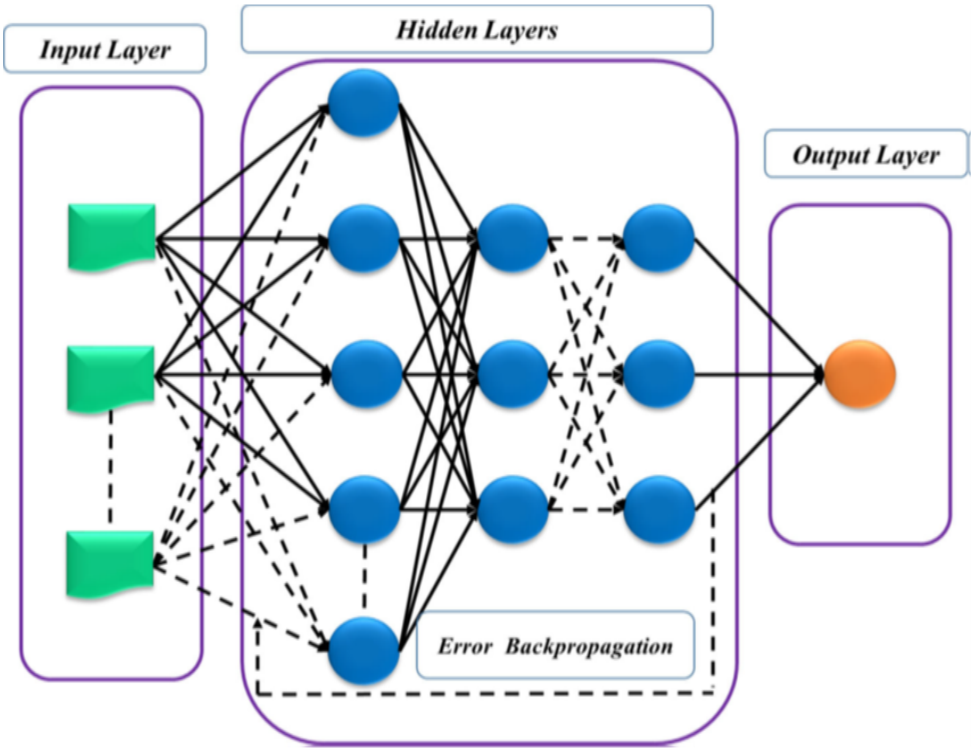


Figure 2.2: Architecture of a basic artificial neural network (ANN). [29]

2.5 Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a type of deep learning model designed for processing data with a grid-like structure, such as images. It is inspired by the organization of the animal visual cortex [30] [31] and is engineered to automatically and adaptively learn spatial hierarchies of features, ranging from low- to high-level patterns. A CNN typically consists of three types of layers: convolution, pooling, and fully connected layers. The convolution and pooling layers are responsible for feature extraction, while the fully connected layer maps these extracted features to the final output, such as classification.

The convolution layer is crucial in CNNs and comprises a series of mathematical operations, primarily convolution, which is a specialized linear operation. In digital images, pixel values are stored in a two-dimensional (2D) grid, or an array of numbers (Fig. 2.4). A small grid of parameters, known as a kernel, acts as an optimizable feature extractor and is applied to each position in the image. This approach makes CNNs highly efficient for image processing, as features can be detected regardless of their location in the image. As each layer passes its output to the next, the extracted features become hierarchically and progressively more complex.

The process of optimizing parameters, such as kernels, is called training. This is done to minimize the difference between the outputs and the ground truth labels using optimization algorithms like backpropagation and gradient descent, among others. [32]

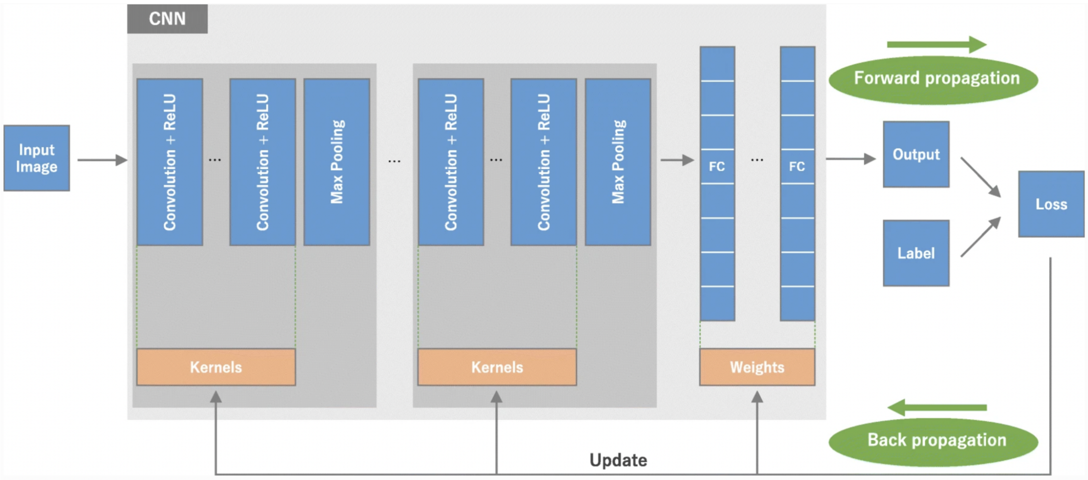


Figure 2.3: Typical CNN architecture. [32]

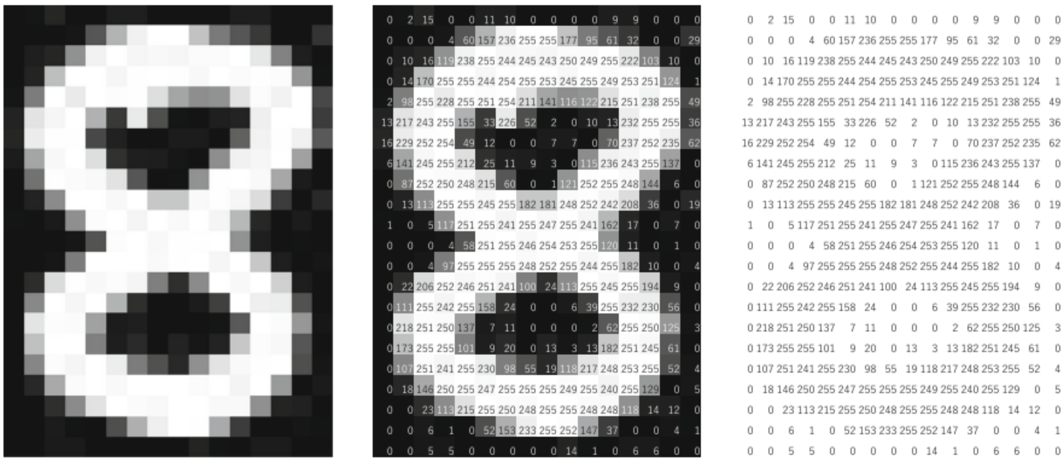


Figure 2.4: A computer sees an image as an array of numbers. The matrix on the right contains numbers between 0 and 255, each of which corresponds to the pixel brightness in the left image. Both are overlaid in the middle image. [32]

2.5.1 Building blocks of CNN architecture

CNN architectures consist of multiple building blocks, such as convolutional layers, pooling layers, and fully connected layers. A typical architecture consists of multiple stacked iterations of convolutional and pooling layers, followed by one or more fully connected layers. The step by which input data is transformed into output through these layers is called forward propagation (Figure 2.3). Although the convolution and pooling operations described in this section apply to 2D CNNs, similar operations can be performed on three-dimensional (3D) CNNs.

2.5.1.1 The Convolution Layer

The CONV layer is the central building block of a convolutional neural network. The parameters of a CONV layer consist of a set of K learnable filters (i.e., "kernels"), where each filter has a width and a height, and is almost always square. These filters are small (relative to their spatial dimensions), but extend across the depth of the volume.

For the input to a CNN, the depth is the number of channels in the image (i.e., a depth of 3 when processing RGB images, one per channel). For volumes deeper in the network, the depth is the number of filters applied in the previous layer.

To make this concept clearer, let's consider the forward pass of a CNN, where we convolve each of the K filters over the width and height of the input volume. More simply, we can imagine each of the K kernels sliding over the input space, computing element-wise multiplications, summing them, and then storing the output values in a 2D activation map. [33]

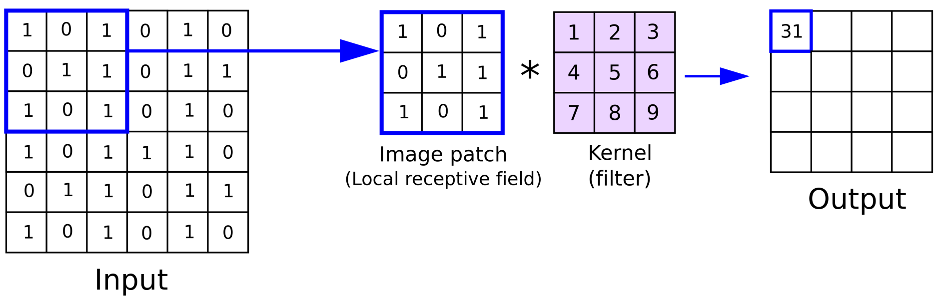


Figure 2.5: Convolution masking. [34]

There are three parameters that control the size of an output volume: the depth, stride, and zero-padding size, each of which we'll review below:

- **Depth (D):** The depth of the output volume controls the number of neurons (i.e.

filters) in the CONV layer that are connected to local regions of the input volume. Each filter creates an activation map that is "activated" in the presence of aligned edges, blobs, or colors. For a given CONV layer, the activation map has a depth of K, or simply the number of filters we have learned in the current layer. The set of filters that "look" at the same (x,y) position of the input is called a depth column.

• **Stride (S):** is how far the filter moves in every step along one direction.For example, using S = 1, our kernel slides from left-to-right and top-to-bottom, one pixel at a time. However, if we were to apply the same operation, only this time with a stride of S = 2, we skip two pixels at a time (two pixels along the x-axis and two pixels along the y-axis), producing a smaller output volume.

• **Padding (P):** Using zero padding, we can "pad" the input around the edges so that the size of the output volume matches the size of the input volume. The amount of padding we apply is controlled by the P parameter. Without zero padding, the spatial dimensionality of the input volume would decrease too quickly and we would not be able to train a deep network (because the input volume would be too small to learn useful patterns from it).

all these parameters together, we can compute the size of an output volume as a function of the input volume size (W, assuming the input images are square, which they nearly always are), the receptive field size F, the stride S, and the amount of zero-padding P. To construct a valid CONV layer, we need to ensure the following equation is an integer:

$$((WF + 2P)/S) + 1 \tag{2.1}$$

2.5.1.2 The Pooling Layer

Pooling layers, also known as downsampling, perform dimensionality reduction, reducing the number of parameters in the input. Similar to convolutional layers, pooling uses a filter that searches across the input, but the difference is that this filter has no weights. Instead, the kernel applies an aggregation function to the values in the receptive field and fills the output array. There are two main types of pooling:

• Max pooling: As the filter moves across the input, it selects the pixel with the largest value to send to the output array. Apart from this, this method tends to be used more frequently compared to average pooling.

• Average pooling: As the filter moves across the input, it calculates the average value within the receptive field to send to the output array.

Although pooling layers lose a lot of information, it also provides many advantages to CNNs. They help reduce complexity, improve efficiency, and limit the risk of overfitting.

[33]

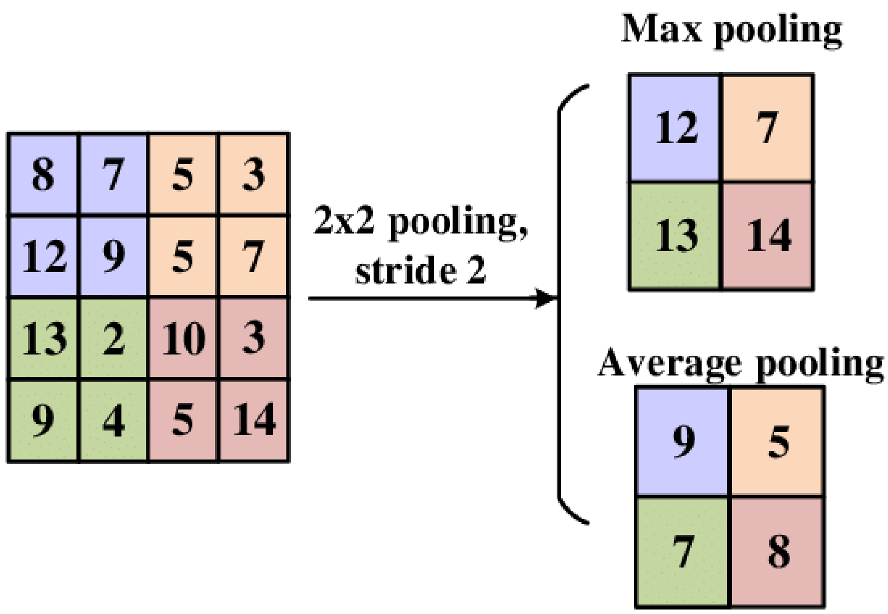


Figure 2.6: Pooling Layer. [35]

2.5.1.3 The Fully-Connected Layer

The output feature maps from the final convolution or pooling layer are typically flattened into a one-dimensional (1D) array or vector. This vector is then connected to one or more fully connected layers, also known as dense layers, where each input is linked to every output via a learnable weight. The features extracted by the convolution layers and downsampled by the pooling layers are subsequently mapped by a series of fully connected layers to produce the network's final outputs, such as the probabilities for each class in classification tasks. The final fully connected layer usually has the same number of output nodes as the number of classes. Each fully connected layer is followed by a nonlinear activation function, such as ReLU. [33]

Table 2.1: A list of parameters and hyperparameters in a convolutional neural network (CNN)

	Parameters	Hyperparameters
Convolution layer	Kernels	Kernel size, number of kernels, stride, padding, activation function.
Pooling layer	Nones	Pooling method, filter size, stride, padding.
Fully connected layer	Weights	Number of weights, activation function.
Others		Model architecture, optimizer, learning rate, loss function, batch-size, epochs, regularization, weight initialization, dataset splitting.

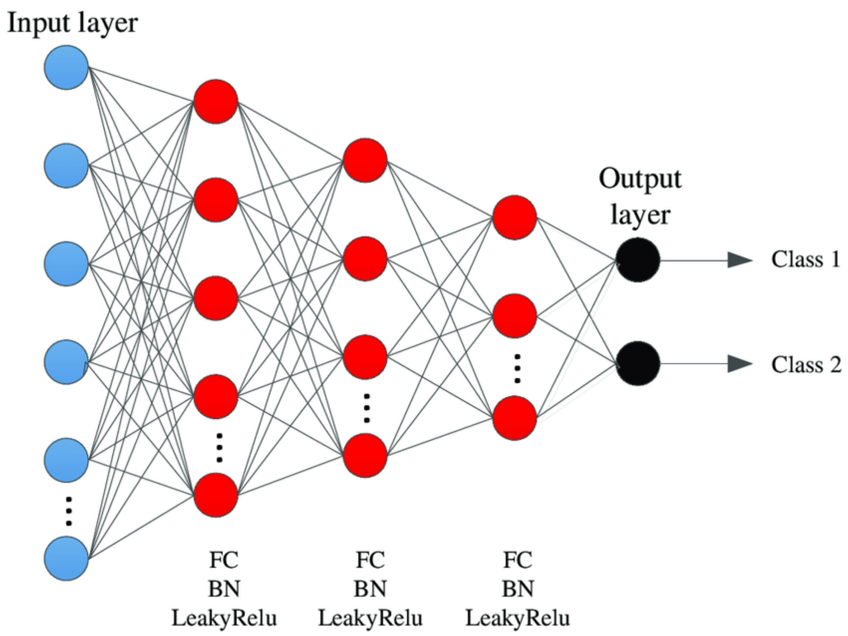


Figure 2.7: Fully-Connected Neural Network [36]

2.5.2 Loss Function

A loss function, sometimes called a cost function, evaluates the agreement between the network's output predictions generated via forward propagation and the provided ground truth labels. The cross entropy function is often used the loss function for multiclass classification, while mean squared error is commonly used for regression tasks involving continuous values. Selecting the appropriate loss function is a crucial hyperparameter decision that is dependent on the specific task at hand. [32]

2.5.3 Gradient Descent

Gradient descent serves as a widely used optimization algorithm that cyclically adjusts the network's learnable parameters (e.g., kernels and weights) to reduce the loss. The gradient of the loss function indicates the direction where the function experiences the sharpest ascent. Consequently, each learnable parameter is modified in the opposite direction of the gradient using a user-defined step size determined by the learning rate hyperparameter (See Fig 2.8). In mathematical terms, the gradient is a partial derivative of the loss concerning each learnable parameter. An individual parameter update is expressed as follows:

$$w := w - \alpha * \frac{\partial L}{\partial w} \tag{2.2}$$

where w stands for each learnable parameter, α stands for a learning rate, and L stands for a loss function. [37] [38]

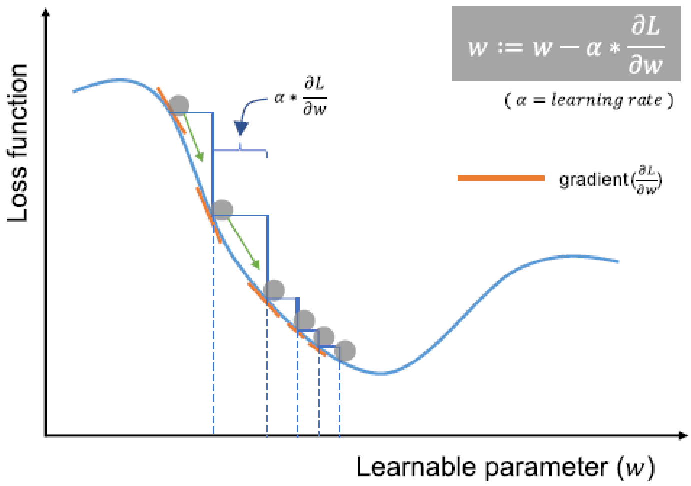


Figure 2.8: Gradient descent is an optimization algorithm that iteratively updates the learnable parameters to minimize the loss, which measures the discrepancy between an output prediction and a ground truth label. The gradient of the loss function indicates the direction of the steepest increase in the function, and all parameters are updated in the opposite direction of the gradient, with the step size determined by a learning rate. [32]

2.5.4 Initialization

Successfully training a ConvNet using a gradient-based method without proper initialization is extremely challenging. ConvNets consist of two sets of parameters: weights and biases. Typically, biases are initialized to zero. This section will outline several techniques for weight initialization that have shown positive results in real-world applications. [39]

1. All Zero: The typical approach to initializing weights involves setting them all to zero. However, this method is ineffective because it causes all neurons to generate identical signals during backpropagation, resulting in weights being updated using the same rule. As a result, the ConvNet will not be trained effectively.

2. Random Initialization: It is more appropriate to randomly initialize the weights. The random values can be selected from either a Gaussian distribution or a uniform distribution. The objective is to create small random numbers. Typically, the mean of the Gaussian distribution is set at 0 and its variance is fixed at a small value like 0.001. An alternative approach is to generate random numbers from a uniform distribution with the minimum and maximum values close to zero, such as $\pm$ 0.001. This method ensures that each neuron will yield distinct outputs during the forward pass. Consequently, the update rule for each neuron will vary from that of the others, leading to appropriate training of the ConvNet.

2.5.5 Dropout

Dropout (Hinton 2014) is a regularization technique used to prevent neural networks from overfitting. For each neuron, a random number between 0 and 1 is generated. If this number is less than a threshold p, the neuron and its connections are dropped from the network. The forward and backward passes are then computed on this modified network. This dropout process is repeated for every sample in the training set, ensuring that different neurons are dropped out in each iteration [39]

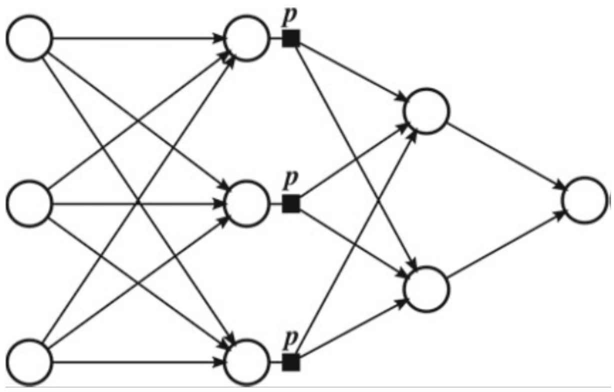


Figure 2.9: If dropout is activated on a layer, each neuron in the layer will be attached to a blocker. The blocker blocks information flow in the forward pass as well as the backward pass (i.e., backpropagation) with probability p. [39]

2.5.6 CNN Architectures

One of the most prominent deep learning architectures for computer vision problems is convolutional neural networks (CNNs). To summarize the different types of CNN architectures described above in an easy to remember form:

Table 2.2: A detailed summary about CNN architectures.

Architecture	**Year**	**Key features**	**Use case**
LeNet	1998	First successful applications of CNNs, 5 layers (alternating between convolutional and pooling), Used tanh/sigmoid activation functions	Recognizing handwritten and machine-printed characters
AlexNet	2012	Deeper and wider than LeNet, Used ReLU activation function, Implemented dropout layers, Used GPUs for training.	Large-scale image recognition tasks.
VGGNet	2014	Deeper networks with smaller filters (33), All convolutional layers have the same depth, Multiple configurations (VGG16, VGG19).	Large-scale image recognition.
GoogLeNet	2014	Introduced Inception module, which allows for more efficient computation and deeper networks, multiple versions (Inception v1, v2, v3, v4).	Large-scale image recognition, won 1st place in the ILSVRC 2014
ResNet	2015	Introduced "skip connections" or "shortcuts" to enable training of deeper networks, Multiple configurations (ResNet-50, ResNet-101, ResNet-152).	Large-scale image recognition, won 1st place in the ILSVRC 2015
DenseNet	2016	Dense connectivity between layers for feature reuse	
MobileNet	2017	Designed for mobile and embedded vision applications, Uses depthwise separable convolutions to reduce the model size and complexity	Mobile and embedded vision applications, real-time object detection
Regnet	2020	Combines the advantages of manual design and NAS.REGENCY-400MF only uses 4.3 million parameters to reach a similar result of EfficientNet-B0.	Design space design.

In our work, we focused on utilizing the following MobileNet :

2.6 MobileNet

The MobileNet architecture, introduced by Howard et al. [40], is designed using depthwise separable convolutions to create a lightweight deep convolutional neural network (CNN). This design significantly reduces the model's size and computation time. The details in the table below illustrate the MobileNet architecture. Consequently, MobileNet is suitable for various recognition tasks such as object detection, face attributes, fine-grained classification, and landmark recognition. [41]

Below is architecture table of MobileNet:

Table 2.3: MobileNet Body Architecture

Type/Stride	**Filter Shape**	**Input Size**
Conv / s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$
Conv dw / s1	$3 \times 3 \times 32dw$	$112 \times 112 \times 32$
Conv / s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$
Conv dw / s2	$3 \times 3 \times 64dw$	$112 \times 112 \times 64$
Conv / s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$
Conv dw / s1	$3 \times 3 \times 128dw$	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$
Conv dw / s2	$3 \times 3 \times 128dw$	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$
Conv dw / s1	$3 \times 3 \times 256dw$	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$
Conv dw / s2	$3 \times 3 \times 256$	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 5512$	$14 \times 14 \times 256$
5 x Conv dw/ s1 5 x Conv / s1	$3 \times 3 \times 512dw$ $1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$ $14 \times 14 \times 512$
Conv dw / s2	$3 \times 3 \times 512dw$	$14 \times 14 \times 512$
Conv / s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$
Conv dw / s2	$3 \times 3 \times 1024dw$	$7 \times 7 \times 1024$
Conv / s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$
Avg Pool / s1	Pool 7×7	$7 \times 7 \times 1024$
FC / s1	1024×1000	$1 \times 1 \times 1024$
Softmax/ s1	Classifer	$1 \times 1 \times 1000$

2.6.1 MobileNet Architectures

2.6.1.1 MobileNet V1

Howard et al. (2017) introduced a class of efficient models called MobileNets (v1), which utilize two simple global hyperparameters to effectively balance latency and accuracy. For instance, on the ImageNet dataset, the MobileNet (v1) model has only 4.2 million parameters, compared to VGG16's 138 million, with a marginal accuracy difference of just 0.9%. However, the structure of MobileNet v1 is similar to that of VGG, and it is less performant compared to architectures like ResNet and DenseNet. The depthwise convolution significantly reduces computational costs. The N x N depthwise plus 1 x 1 pointwise structure achieves performance close to that of the N x N convolution. In practice, the kernel of the depthwise part is often discarded during training, resulting in many empty kernels. [42]

Table 2.4: MobileNet-V1 Architecture

Layer Name	Input	Block Operator	c	n	s
Input Image	$224 \times 224 \times 3$	Conv2d	32	1	2
Conv 1	$112 \times 112 \times 32$	Depth Wise Conv	64	1	1
	$112 \times 112 \times 64$	Depth Wise Conv	128	1	2
Conv 2	$56 \times 56 \times 128$	Depth Wise Conv	128	1	1
	$56 \times 56 \times 128$	Depth Wise Conv	256	1	2
Conv 3	$28 \times 28 \times 256$	Depth Wise Conv	256	1	1
	$28 \times 28 \times 256$	Depth Wise Conv	512	1	2
Conv 4	$14 \times 14 \times 512$	Depth Wise Conv	512	5	1
	$14 \times 14 \times 512$	Depth Wise Conv	1024	1	2
Conv 5	$7 \times 7 \times 1024$	Depth Wise Conv	1024	1	1
	$7 \times 7 \times 1024$	Depth Wise Conv	-	-	-

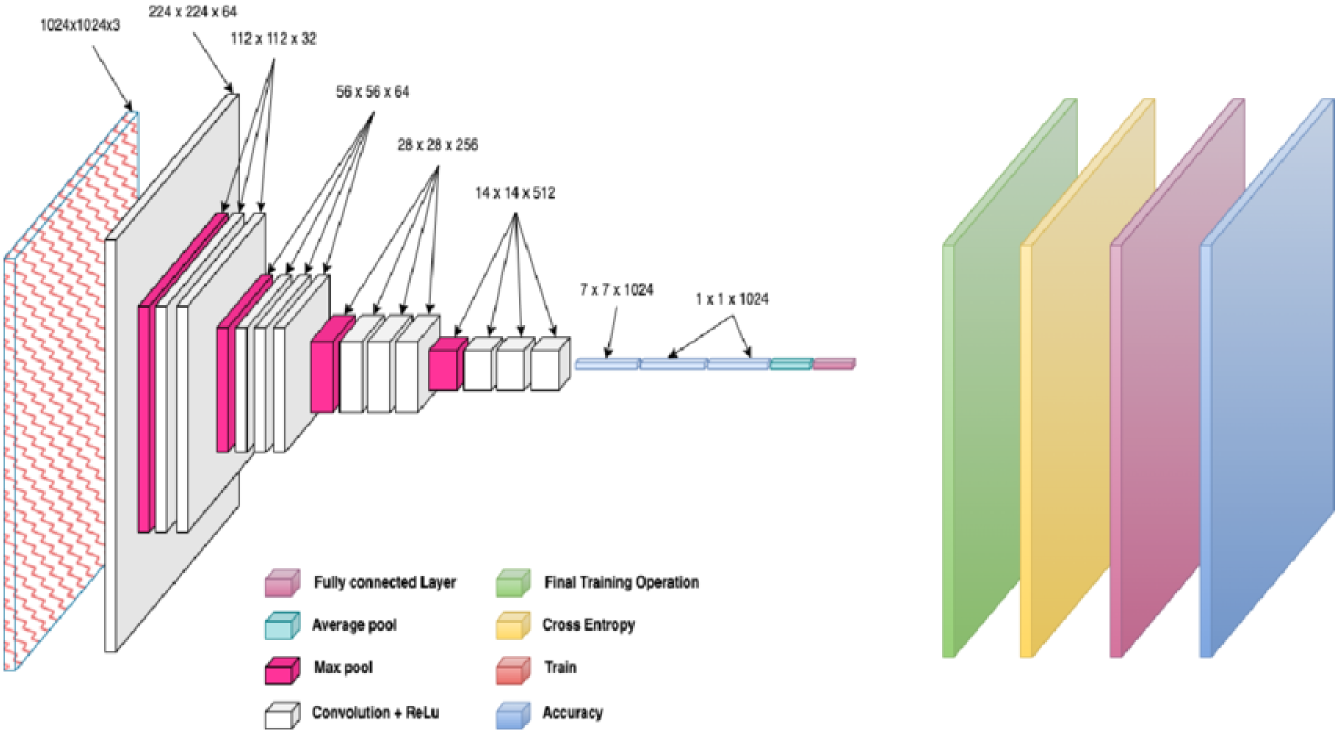


Figure 2.10: MobileNet-V1 architecture. [43]

2.6.1.2 MobileNet V2

Sandler et al. (2018) introduced MobileNetV2, a neural network designed to enhance MobileNetV1 in two key areas. Firstly, they introduced a linear bottleneck that employs linear activation instead of ReLU to prevent the loss of information in the nonlinear layer. Additionally, inspired by ResNet, they implemented inverted residuals to improve gradient propagation between layers, resulting in higher memory efficiency. [42]

Input	Operator	t	c	n	s
$224^2 \times 3$	conv2d	-	32	1	2
$112^2 \times 32$	bottleneck	1	16	1	1
$112^2 \times 16$	bottleneck	6	24	2	2
$56^2 \times 24$	bottleneck	6	32	3	2
$28^2 \times 32$	bottleneck	6	64	4	2
$14^2 \times 64$	bottleneck	6	96	3	1
$14^2 \times 96$	bottleneck	6	160	3	2
$7^2 \times 160$	bottleneck	6	320	1	1
$7^2 \times 320$	conv2d 1×1	-	1280	1	1
$7^2 \times 1280$	avg pool 7×7	-	-	1	-
$1 \times 1 \times 1280$	conv2d 1×1	-	k	-	-

Table 2.5: MobileNetV2: Each line describes a sequence of 1 or more identical (modulo stride) layers, repeated n times. All layers in the same sequence have the same number c of output channels. The first layer of each sequence has a stride s and all others use stride 1. All spatial convolutions use 33 kernels. The expansion factor t is always applied to the input size.

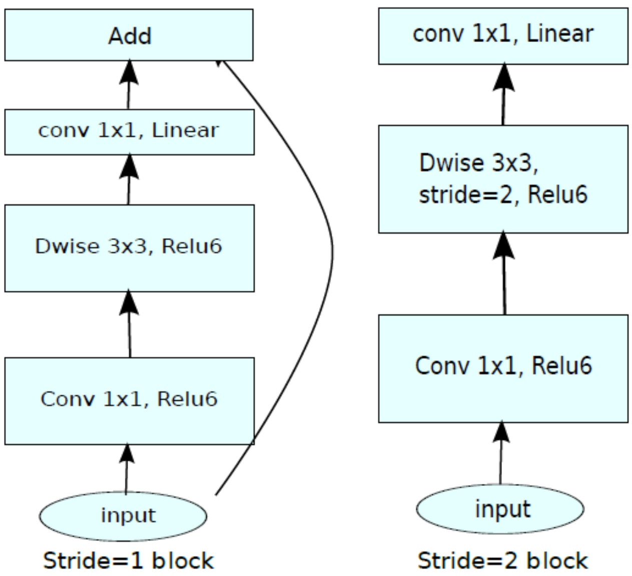


Figure 2.11: MobileNetV2 architecture. [44]

2.6.1.3 MobileNet V3

Howard et al. (2019) introduced MobileNetV3 in two versions: MobileNetV3-Small and MobileNetV3-Large, each with different computation and storage requirements. MobileNetV3 utilizes network architecture search (NAS) and the NetAdapt algorithm to enhance performance. MobileNetV3-Large improves accuracy by approximately 3.2% over MobileNetV2 in ImageNet classification tasks while reducing computation time by 20%. Compared to MobileNetV3-Small, it improves accuracy by 6.6% with similar latency. Additionally, MobileNetV3-Large achieves the same accuracy on COCO detection tasks and is 25% faster than MobileNetV2. [42]

Input	**Operator**	**exp size**	**out**	**SE**	**NL**	**s**
$224^2 \times 3$	conv2d, 3×3	-	16	-	HS	2
$112^2 \times 16$	bneck, 3×3	16	16	✓	RE	2
$56^2 \times 16$	bneck, 3×3	72	24	-	RE	2
$28^2 \times 24$	bneck, 3×3	88	24	-	RE	1
$28^2 \times 24$	bneck, 5×5	96	40	✓	HS	2
$14^2 \times 40$	bneck, 5×5	240	40	✓	HS	1
$14^2 \times 40$	bneck, 5×5	240	40	✓	HS	1
$14^2 \times 40$	bneck, 5×5	120	48	✓	HS	1
$14^2 \times 48$	bneck, 5×5	144	48	✓	HS	1
$14^2 \times 48$	bneck, 5×5	288	96	✓	HS	2
$7^2 \times 96$	bneck, 5×5	567	96	✓	HS	1
$7^2 \times 96$	bneck, 5×5	576	96	✓	HS	1
$7^2 \times 96$	conv2d 1×1	-	576	✓	HS	1
$7^2 \times 576$	pool 7×7	-	-	-	-	1
$1^2 \times 576$	conv2d 1×1, NBN	-	1024	-	HS	1
$1^2 \times 1021$	conv2d 1×1, NBN	-	k	-	-	1

Table 2.6: MobileNet V3 architecture.

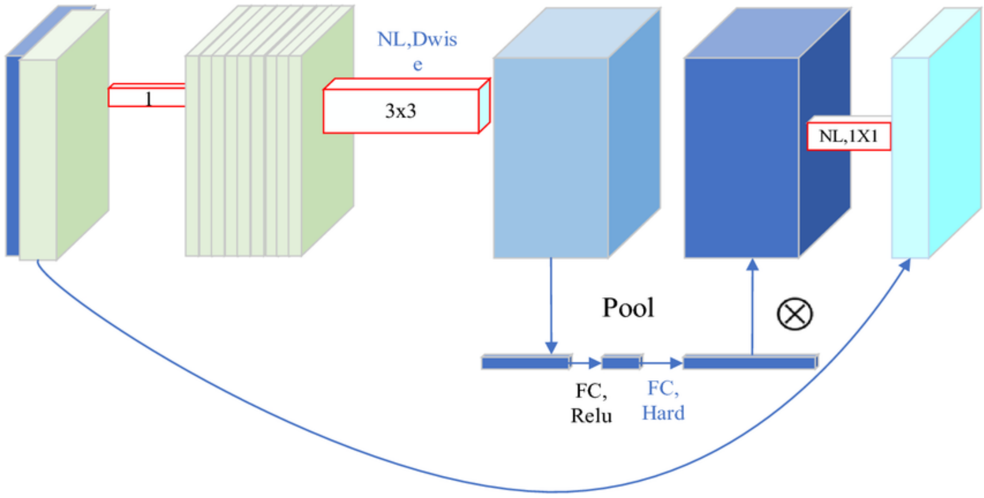


Figure 2.12: Structure of MobileNet-V3 Model. [45]

2.7 Performance Evaluation

2.7.1 Cross Entropy Loss (Loss function)

Or log loss, is a measure used in classification models performance evaluation and it is found in the machine learning, deep learning. It assesses how well the model matches the actual labels by comparing the predicted probability distribution of the target classes with the true probability distribution. Lower values of cross-entropy mean better model performance; Cross-entropy is given by:

$$L_{CE} = -\sum_{i=1}^{n} t_i \log(p_i) \tag{2.3}$$

n : Nombre of class.
t_i : Truth label
p_i : The softmax probability for the i^{th} class.

2.7.2 Multi class Accuracy (Accuracy)

Accuracy (or multi-class accuracy) is used to gauge the success rate of classification in the realm of machine learning or deep learning models, particularly when dealing with datasets that comprise multiple classes or categories. It quantifies the volume of accurately classified cases against all other cases within the dataset.
To put it mathematically, accuracy is determined by taking the number of correctly predicted instances and dividing this by the total count of instances:

$$MulticlassAccuracy = \frac{C}{N} \times 1000 \tag{2.4}$$

C : Total number of correct predictions.
N : The total number of instances or samples in the dataset.

2.7.3 Recall (aka Sensitivity)

Recall is another name for sensitivity or true positive rate. It is used as a performance metric in binary classification and multi-class classification tasks. Recall measures the capability of a model to identify all relevant instances correctly from a dataset, especially the proportion of true positive instances that were accurately classified out of all actual positive instances.
Mathematically, recall is computed by taking the number of true positive predictions

divided by the sum of true positive predictions and false negative predictions:

$$Sensitivity = \frac{TP}{TP + FN} \tag{2.5}$$

FN : False negative (The number of instances incorrectly predicted as negative).
TP : True positive (The number of instances correctly predicted as positive).

2.7.4 Precision

Precision is an indication of how well a classification model is doing in finding only the relevant instances. It is given by the ratio of true positive predictions to the sum of true positives and false positives, thereby reflecting accuracy for positive predictions.

From a mathematical standpoint, precision is denoted by the formula:

$$Precision = \frac{TP}{TP + FP} \tag{2.6}$$

FP : False positive (The number of instances incorrectly predicted as positive).
TP : True positive (The number of instances correctly predicted as positive).

F1-score(F-measure)

The F1-score is used as an assessment metric for a classification model; it stands for the harmonic mean of precision and recall. It offers a balance between these two concerns: precision and recall are both equally important, but when you want to achieve a balance between both, consider using the F1-score since it is more useful than either of them individually. This happens when there is an imbalance in the class distribution: so if you need to take into account not only the imbalances in class numbers but also the rate at which each type of error should be minimized, then go with F1.

From a mathematical standpoint, F1-score is denoted by the formula:

$$F1 - score = \frac{2 \cdot Prcision \cdot Recall}{Prcision + Recall} \tag{2.7}$$

2.7.5 Support

The support is defined as the number of actual occurrences of a class in the dataset, an essential metric that gives meaning to other evaluation metrics including precision, recall and F1-score, since it tells how many instances of each class are present and used for evaluation.

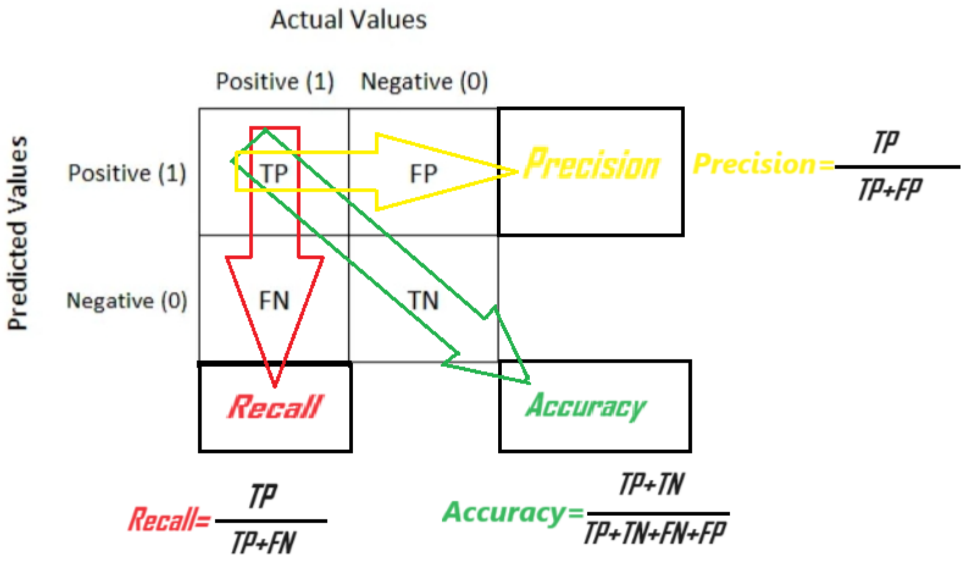


Figure 2.13: Confusion Matrix

2.7.6 AUC (Area Under the Curve)

In deep learning, AUC stands for Area Under the Curve, a metric used to evaluate the performance of binary classification models. It summarizes the model's ability to distinguish between positive and negative classes.

2.8 Conclusion

The previous sections aimed to provide a comprehensive overview of the main concepts behind deep learning algorithms, extending beyond basic understanding. We began with a comparison between "deep learning" and "machine learning", followed by a brief definition of artificial neural networks (ANN). This was complemented by a detailed analysis of convolutional neural networks (CNN). Additionally, we explored popular CNN architectures, with a focus on the MobileNet models and outlined their general architectures. The goal of this section was to equip the reader with the necessary background information to understand the experimental results discussed later in the paper.

Chapter 3

Experimental Results

3.1 Introduction

In this section, we present the experimental results of our approach using the Keras neural network model to verify the date fruit . Our study aims to evaluate the effectiveness of our approach in verifying the classification of different types of date fruits. We provide a comprehensive analysis of the performance of our approach, including paging, Roc, and accuracy. In addition, we describe the experimental protocol used, which includes the data sets used . Finally, we offer In-depth discussion of the results obtained, highlighting their relevance and practical implications.

3.2 Work Environment

3.2.1 Hardware Environment:

In this section we present the hardware environment used for the application, the characteristics are: a **LENOVO** PC:

- Processor:Intel(R) Core(TM) i7-8650U CPU @ 1.90GHz (8 CPUs), 2.1 GHz.
- Installed RAM: 8.00 GB.
- Hard Drive : 256 GB SSD.
- System Type 64-bit operating system, x64-based processor.
- OS: Windows 11 Pro.

3.2.2 Software Environment:

Visual Studio Code

- Visual Studio Code 1.89.1 version was installed on the laptop, which included the Python 3.
- Python 3.11, NumPy, open-cv, pandas, tensorflow, seaborn, sklearn and Matplotlib were installed through VS code to handle data manipulation, analysis, and visualization tasks.

Thonny:

- Thonny 4.1.4 version was installed on raspberry pi,which included the python 3.
- Python 3.12.3 , numPy, pandas, Scikit-learn, TensorFlow, and Matplotlib and open-cv came already installed, and other Python libraries could be installed through built-in commands.

3.3 Tools Used

Os

Python's os library offers a means of engaging with the operating system, enabling users to carry out a range of tasks related to the operating system. These tasks include but are not limited to: generating and removing directories and files, manipulating file paths, and executing system commands.

Matplotlib

Matplotlib is a powerful tool for visualizing data that is built on the Numpy and Scipy frameworks and can be utilized on multiple platforms. One of the primary benefits of Matplotlib is its compatibility with a variety of operating systems and graphics interfaces. [46]

Pandas

The Pandas library in Python is specifically intended for analyzing and modifying data, this data is stored in data structures that are highly effective at storing large amounts of data. It features a comprehensive set of tools that transform, analyze, and purges your data in order to ensure accurate results. [47]

Tensorflow

TensorFlow utilizes programming languages such as Python and R, employing data flow graphs to handle data as it progresses through the neural network. Building machine learning models with TensorFlow is a straightforward process, enabling the creation of robust models for production purposes and facilitating extensive experimentation for research purposes. Additionally, TensorFlow offers the advantage of TensorBoard, a tool for visualizing data.

Keras

Keras, initially created by Francois Chollet, has experienced rapid growth as a deep learning framework package . The appeal of Keras lies in its support for a high-level neural network API, which is implemented in Python. Notably, Keras operates seamlessly on TensorFlow, Theano, and CNTK. This versatile framework has found applications in numerous startups, research laboratories, and prominent organizations such as Microsoft Research, NASA, Netflix, and Cern.

Numpy

A cornerstone library in Python for scientific computation is NumPy (Numerical Python). With these arrays, NumPy presents robust options for handling multi-dimensional entities and matrices along with a wide repertoire of high-level mathematical functions that are purposefully designed to facilitate efficient operations on the arrays.

Open CV

OpenCV (Open Source Computer Vision Library) is a robust open-source library for real-time computer vision applications; it is broadly adopted in the field. It comprises a rich collection of algorithms and tools that cater to an extensive range of tasks related to computer vision.

Pathlib

Pathlib is a built-in Python library. It was introduced in Python 3.4 and offers an object-oriented plus user-friendly approach to file system paths handling. It has several benefits over the typical os (operating system) module for dealing with file paths.

Seaborn

Built on the foundation of Matplotlib, Seaborn is a robust Python library that specializes in crafting statistical data visualizations. Its primary purpose is to streamline the creation of visually appealing and informative plots, which are frequently employed in the realms of data exploration, analysis, and communication

Sklearn.Metrics

The scikit-learn library in Python is home to the highly influential module known as sklearn.metrics. This module boasts an extensive repertoire of functions designed to assess and contrast the effectiveness of various deep learning models, specifically those employed in classification, regression, clustering, and related endeavors.

3.4 Data Augmentation Technique

Data Augmentation Technique stands out as an effective method that fosters the ability of a model to generalize by producing altered replicas of a data collection through the current available information. In some cases, small tweaks are made to the dataset while in other cases modifications can be generated using deep learning algorithms.

The type of data augmentation techniques used:

Rescaling during data augmentation can make your images better prepared for deep learning by standardizing pixel values, leading to more efficient training and potentially better model performance.

The rotation technique is a method of creating new versions of an image by rotating it around its central point. This method is especially useful for applications such as object detection, classification, and mode estimation.

Shear is a method of artificially altering an image by utilizing a shearing operator. This method facilitates the improvement of a model's resilience to changes in image orientation and perspective.

Zoom is a particular technique in the realm of artificially changing the training images, it belongs to the group of geometric transformations. Geometric transformations are related to making changes to the spatial properties of an image data.

3.5 Parameter Settings

In our methodology, we set up the optimizer and learning rate uniformly in all experiments and tweak only one setting before proceeding with others. After each modification of a setting, we reconfigure the rest of the components and then study what comes out of it. This sequential approach allows us to methodically assess how each individual setting influences the final output of the system.

The settings as following :

- Network : MobilNet V2 , VGG-16 , AlexNet.

- Batch-Size : defines the number of input samples that are passed on to the network. Batch size is also an influencing parameter which determines the accuracy of classification. Larger the batch size, more time it takes for the training of dataset, and eventually the accuracy of the model decreases and also affects the memory requirement, Our model is executed with the following batch sizes: 16 , 32 , 64 and 128.

- Epochs : are nothing but the number of iterations. using Adam optimizer this model is trained at epochs: 80 , 100 and 120.

- validation-split : is a technique for partitioning data into training, validation, and test sets. We use two split validation: 0.1 and 0.2 .

3.6 Results and Analysis

Although we conducted thorough and in-depth testing on various datasets available ,but We focused in our analysis on present the results from one database.

3.6.1 Effect of Network:

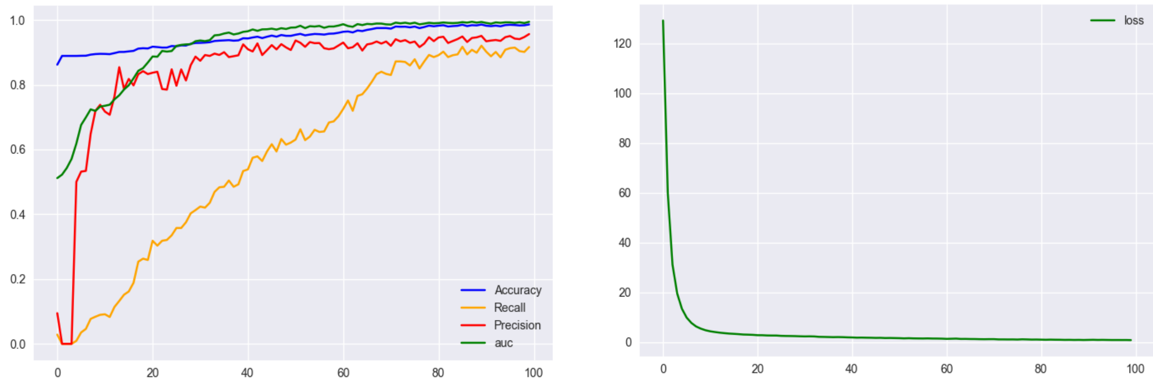
In this step, We have installed the necessary Settings and made modifications to the network by selecting from options such as MobilNet V2,AlexNet and VGG-16.

3.6.1.1 1- MobilNet V2

Table 3.1: Accuracy (%) on Mobilenet V2 Network for Used Database

Database	Mobilnet V2 network			
	Epoch	**Batch-size**	**Validation split**	**Accuracy**
dataset-9	80	16	0.1	92
dataset-9	80	32	0.1	95
dataset-9	80	64	0.1	95
dataset-9	80	64	0.2	92
dataset-9	100	32	0.1	**98.96**

Taking into account the difference in accuracy of the network results in the studied database, based on the obtained results we can conclude that the Mobilenet version 2 network has superior performance in terms of accuracy at Epoch 100, batch-size 32 and validation-split 0.1, because The depth of network reaches 53 layers, making it a deep network that can learn hierarchical features. As depth increases, the model can learn more complex representations and extract more, more specific features, resulting in higher accuracy.



(a) (b)

Figure 3.1: MobileNet V2 results. (a) The performance metrics curves. (b) Loss curve.

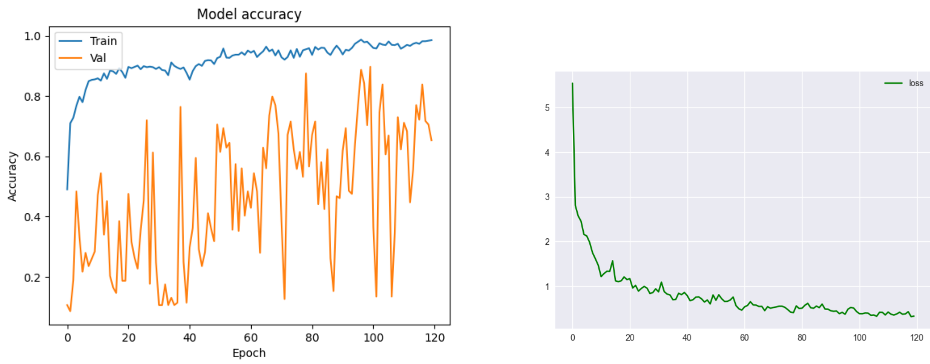
The graph (a) suggests a model that starts with poor recall and precision but quickly improves in precision almost optimally while achieving moderate recall. Accuracy and AUC are consistently high, suggesting overall good model performance, particularly in distinguishing between classes . However, the moderate recall indicates room for improvement in capturing all relevant instances.
The graph (b) shows the course of the "loss function" over 100 epochs.At the beginning of the training process, the curve drops sharply until it proved . This indicates that the model quickly learns a large amount of initial training data, resulting in a significant improvement in performance.
This graph is a useful tool to understand the behavior of the model during training and can guide decisions on how to adjust the training process to achieve better performance.

3.6.1.2 2- Alexnet

Table 3.2: Accuracy (%) on Alexnet Network for Used Database

Database	Alexnet network			
	Epoch	Batch-size	Validation split	Accuracy
dataset-9	80	64	0.2	92
dataset-9	80	128	0.2	93
dataset-9	120	128	0.2	95
dataset-9	120	32	0.2	**98.5**
dataset-9	120	32	0.1	95

Taking into account the difference in the accuracy of the network results in the studied database, based on the results obtained, we can conclude that the AlexNet network has superior performance in terms of accuracy in the Epoch of 120, batch size 32 and validation split 0.2 .The results indicate that fine - tuning of Epoch , Batch size and Validation split can significantly affect the performance of the model.



(a) (b)

Figure 3.2: AlexNet curves. (a) Train and Valid Accuracy. (b) Loss curve.

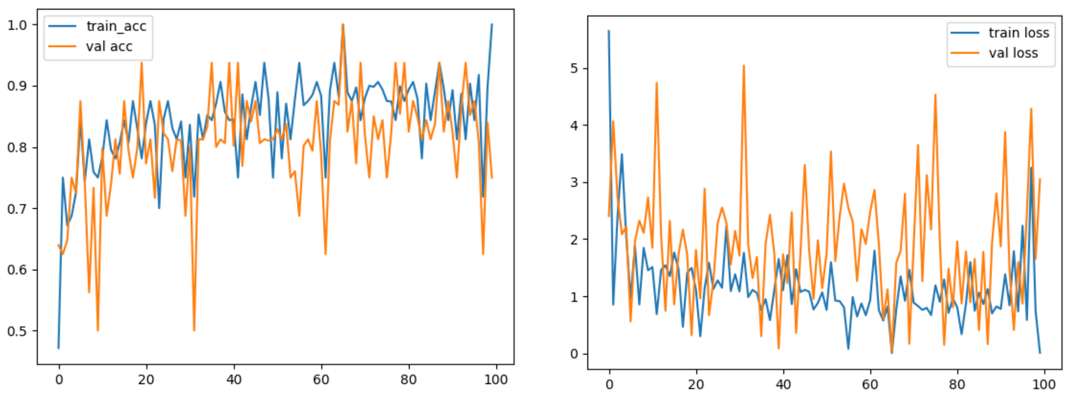
Graph (A) shows changes in accuracy, while the model achieves high accuracy on the training data, its performance on the validation data is highly unstable, indicating overfitting. Implementing strategies to improve stability in validation performance is critical to robust model development. Graph (B) illustrates the progression of the "loss function" over 120 epochs. At the start of the training process, the function's slope is high, this suggests that the model has learned effectively and minimized the loss during the training period. A rapid decrease in loss that is followed by a flat increase indicates that the model has a well-converged profile and achieves a stable state of low loss, which is indicative of good training performance.

3.6.1.3 3- VGG16

Table 3.3: Accuracy (%) on VGG-16 Network for Used Database

Database	VGG-16 network			
	Epoch	**Batch-size**	**Validation split**	**Accuracy**
dataset-9	80	16	0.1	81.66
dataset-9	80	32	0.1	82.66
dataset-9	80	64	0.1	82.23
dataset-9	80	64	0.2	83
dataset-9	100	32	0.1	**85.08**

Taking into account the difference in the accuracy of the network results in the studied database, based on the results obtained, we can conclude that the VGG 16 network hassuperior performance in terms of accuracy in the Epoch of 100, batch size 32 and validation split 0.1 .The results indicate that fine tuning of Epoch , Batch size and Validation split can significantly affect the performance of the model.



(a) (b)

Figure 3.3: VGG-16 curves. (a) Train and Valid Accuracy.(b) Train and Valid Loss.

The graph (a) demonstrates the changes in accuracy, while the model's accuracy is high in the training data, and their performance on the validation data is very erratic, which suggests that they have been overfitted.The evolution of the "loss function" over 100 epochs is depicted in graph (B). It is evident that there are fluctuations in both the training losses and model validation, despite the overall decrease over time. These fluctuations suggest instability in the learning process.

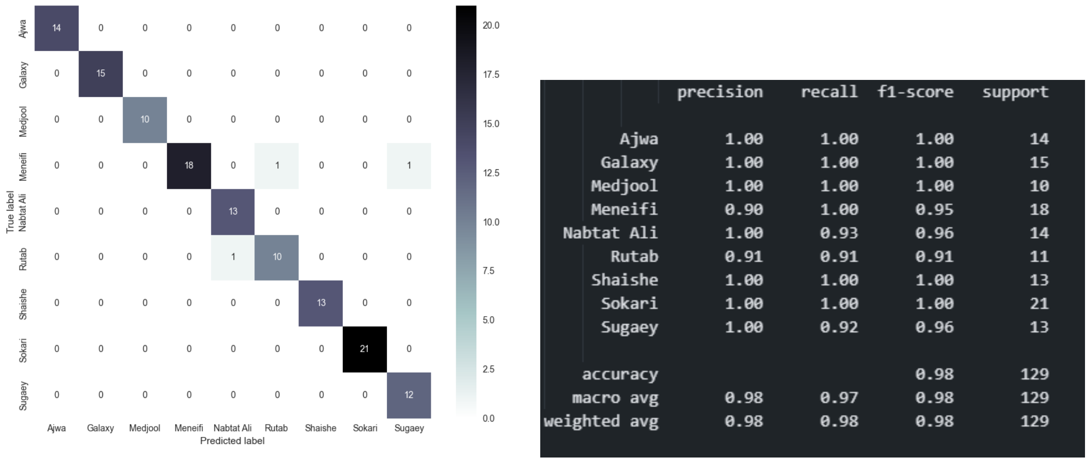
3.6.2 Best Results and Settings

Our experiments revealed that the Mobilnet v2 network achieved the best results. The figure below shows the performance of our proposed approach for different types of date fruit.

Database	Mobilnet V2 network
Dataset-9	98.96
Dataset-20	97

Table 3.4: Accuracy (%) on Mobilnet V2 Network for Used Databases

Through the results obtained from a different dataset , we found that dataset-9 is better in accuracy than dataset-20.



	precision	recall	f1-score	support
Ajwa	1.00	1.00	1.00	14
Galaxy	1.00	1.00	1.00	15
Medjool	1.00	1.00	1.00	10
Meneifi	0.90	1.00	0.95	18
Nabtat Ali	1.00	0.93	0.96	14
Rutab	0.91	0.91	0.91	11
Shaishe	1.00	1.00	1.00	13
Sokari	1.00	1.00	1.00	21
Sugaey	1.00	0.92	0.96	13
accuracy			0.98	129
macro avg	0.98	0.97	0.98	129
weighted avg	0.98	0.98	0.98	129

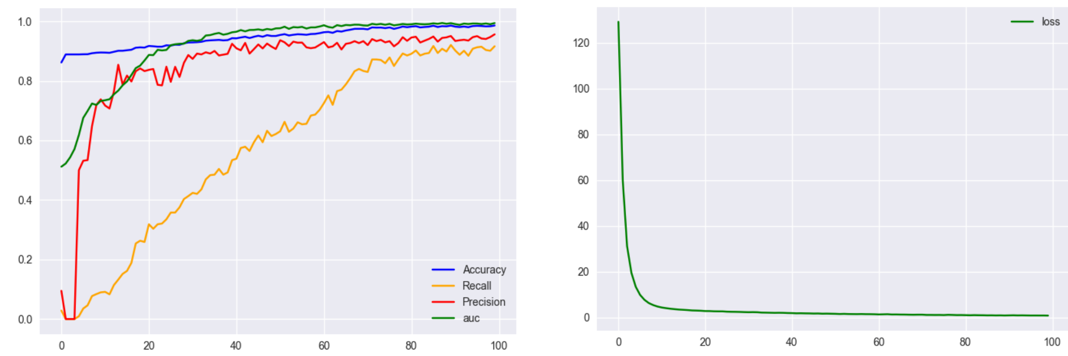
(a) (b)

Figure 3.4: Result of MobilNet V2(with dataset-9)

Our observations indicate that the majority of classes such as Ajwa, Galaxy, Medjool, Shaishe, and Sokari exhibit perfect scores across precision, recall, and F1-score. This points towards an outstanding model performance for these particular classes.

In terms of Meneifi, the precision value stands at 0.90 while the F1-score is 0.95— indicating a slightly lower accuracy level but a reasonable harmonic mean between precision and recall. On the other hand, Rutab shows lesser values for both precision and recall (0.91) when juxtaposed with the other classes; this suggests more misclassifications taking place as either false positives or false negatives.

Our observations indicate that the use of Mobilnet V2 with a Batch-size of 32, Epoch of 100, and Validation-split of 0.1 yielded the best performance in terms of the accuracy .



(a) (b)

Figure 3.5: results of Mobilnet V2

The graph (a) suggests a model that starts with poor recall and precision but quickly improves in precision almost optimally while achieving moderate recall. Accuracy and AUC are consistently high, suggesting overall good model performance, particularly in distinguishing between classes . However, the moderate recall indicates room for improvement in capturing all relevant instances.

Figure (b) shows the course of the "loss function" over 100 epochs.At the beginning of the training process, the curve drops sharply until it proved . This indicates that the model quickly learns a large amount of initial training data, resulting in a significant improvement in performance.

This graph is a useful tool to understand the behavior of the model during training and can guide decisions on how to adjust the training process to achieve better performance.

3.6.3 Comparison with State-of-the-Art Approaches

Compared to other approaches in the literature, our method achieved comparable results across all the date fruit classifications used and outperformed all the listed approaches, as demonstrated in Table 3.5.

Table 3.5: Accuracy of checking the classification

Approach	**Accuracy**
VGG-16 [48]	92.7
VGG-16 [49]	96.98
VGG-16 [50]	88.58
Resnet-50 [51]	88.27
MobileNet [52]	87.96
AlexNet [48]	96.51
AlexNet [53]	94.2
Rf [54]	85
DenseNet201 model [54]	97.21
ANN [55]	98.6
ANN [56]	92.2
LR [56]	91
DNN [57]	97.2
Our approach	**98.96**

3.7 Conclusion

This chapter focuses on verifying the classification of date fruit, in several different grids.

The primer involves training neural networks on date fruit classification datasets, by taking advantage of our protocol with data augmentation technology and using various training methods. Our proposed approach has achieved competitive accuracy compared to the latest modern methods. In addition, we conducted a comprehensive pilot study to analyze the impact of various settings on checking the quality of the classification .

General Conclusion

Technology today is so advanced that machines can perform complex tasks using artificial intelligence. Deep learning is most appropriate for analyzing large amounts of data coming from different sources and extracting information that can be used. In the field of AI, computer vision is identified as the cornerstone of enabling machines to make sense out of digital pictures, videos and other visual data and use that derived intelligence for decision making or recommendations. The project focused on date fruit classification capitalizes on the power of computer vision and deep learning models to accurately categorize dates based on their specific type and quality. The proposed CNN-based model, fine-tuned using the MobileNetV2 architecture and optimized layer composition, represents a significant advancement in the art of date fruit classification, and its ability to accurately classify dates can contribute to various applications in agriculture, food processing, and quality control and improve the efficiency and productivity of the date fruit industry.

In the first chapter, we discussed the basic overview of the date palm and date fruit, including the characteristics of each variety, the countries with the highest production, and the most famous varieties. We also studied the concept of relatedness, especially facial relatedness, and the design of the system, as well as the challenges in this field and its future prospects. Finally, we discussed the database used in this study.

However, the second chapter is about the difference between machine learning and deep learning. Artificial Neural Networks (ANN) are then introduced and Convolutional Neural Networks (CNN) are fully explained with a detailed description of their components and most important structures. We pay special attention to the "MobileNet" architecture, which is the core of our study. We thoroughly examine all iterations of MobileNet and discuss the architecture of each version in detail.

In the final chapter, we trained other CNN methods such as AlexNet, MobileNet, and VGG-16 on the dataset, to improve the performance and accuracy of the model, we also used data augmentation techniques and checked the impact of different settings on the accuracy of our method by changing one hyperparameter at a time and keeping the others constant. We then examined and analyzed the obtained results, and the experimental results showed that the proposed method achieved competitive results compared to other CNN methods.

In summary, most of the goals described in this work have been achieved, but there are still some ideas and possible improvements that can still be achieved in the future, such as:

- Employing thermal cameras, which can detect temperature variations indicative of internal defects such as caries, we can streamline the sorting process without the need for manual inspection or opening of the fruits.
- Other CNNs and recent transformers can also be attempted on our dataset.
- Integrating an intuitive interface will allow operators to control various parameters such as classification speed, sensitivity thresholds, and sorting criteria, resulting in optimizing efficiency and accuracy

Bibliography

[1] Said Awad, Yonghui Zhou, Evina Katsou, Yunfeng Li, and Mizi Fan. A critical review on date palm tree (phoenix dactylifera l.) fibres and their uses in bio-composites. *Waste and biomass valorization*, 12:2853–2887, 2021.

[2] ChihCheng T Chao and Robert R Krueger. The date palm (phoenix dactylifera l.): overview of biology, uses, and cultivation. *HortScience*, 42(5):1077–1082, 2007.

[3] Noemí Echegaray, Beatriz Gullón, Mirian Pateiro, Ryszard Amarowicz, Jane M Misihairabgwi, and José M Lorenzo. Date fruit and its by-products as promising source of bioactive components: A review. *Food Reviews International*, 39(3):1411–1432, 2023.

[4] Hamdi Altaheri, Mansour Alsulaiman, and Ghulam Muhammad. Date fruit classification for robotic harvesting in a natural environment using deep learning. *IEEE Access*, 7:117115–117133, 2019.

[5] Oussama Aiadi, Mohammed Lamine Kherfi, and Belal Khaldi. Automatic date fruit recognition using outlier detection techniques and gaussian mixture models. *ELCVIA Electronic Letters on Computer Vision and Image Analysis*, 18(1):52–75, 2019.

[6] Wadha SN Alhamdan and Jacob M Howe. Classification of date fruits in a controlled environment using convolutional neural networks. In *Advanced Machine Learning Technologies and Applications: Proceedings of AMLTA 2021*, pages 154–163. Springer, 2021.

[7] Oussama Aiadi, Belal Khaldi, Mohammed Lamine Kherfi, Mohamed Lamine Mekhalfi, and Abdullah Alharbi. Date fruit sorting based on deep learning and discriminant correlation analysis. *IEEE Access*, 10:79655–79668, 2022.

[8] Jinu Lilly Joseph, Veena A Kumar, and Santhosh P Mathew. Fruit classification using deep learning. In *Innovations in Electrical and Electronic Engineering: Proceedings of ICEEE 2021*, pages 807–817. Springer, 2021.

[9] Shri Mohan Jain, Jameel M Al-Khayri, and Dennis V Johnson. Date palm biotechnology. 2011.

[10] Sarah Manai, Abdennacer Boulila, Ana Sanches Silva, Letricia Barbosa-Pereira, Raquel Sendón, and Khaoula Khwaldia. Recovering functional and bioactive compounds from date palm by-products and their application as multi-functional ingredients in food. *Sustainable Chemistry and Pharmacy*, 38:101475, 2024.

[11] Ahmed Abu Hanieh, Afif Hasan, and Muhammed Assi. Date palm trees supply chain and sustainable model. *Journal of cleaner production*, 258:120951, 2020.

[12] Abdelouahhab Zaid, E de J Arias-Jimenez, et al. Date palm cultivation. 1999.

[13] https://woodspurfarms.com/dates-a-complete-guide-to-everything-about-the-fruit/.

[14] Dates, deglet noor". Food Data Central. USDA Agricultural Research Service (ARS). Archived from the original on 3 April 2019. Retrieved 25 May 2020.

[15] Walid Al-Shahib and Richard J Marshall. The fruit of the date palm: its possible use as the best food for the future? *International journal of food sciences and nutrition*, 54(4):247–259, 2003.

[16] https://fdc.nal.usda.gov/fdc-app.html/food-details/168191/nutrients.

[17] Nora Abdullah AlFaris, Jozaa Zaidan AlTamimi, Fatima Ali AlGhamdi, Najla Abdullah Albaridi, Riyadh A Alzaheb, Dalal Hamad Aljabryn, Amani Hamzah Aljahani, and Lujain Abdulaziz AlMousa. Total phenolic content in ripe date fruits (phoenix dactylifera l.): A systematic review and meta-analysis. *Saudi Journal of Biological Sciences*, 28(6):3566–3577, 2021.

[18] Xing Chang, Zhenyu Zhao, Wenjin Zhang, Dong Liu, Chunxia Ma, Tian Zhang, Qingyan Meng, Peizheng Yan, Longqiong Zou, and Ming Zhang. Natural antioxidants improve the vulnerability of cardiomyocytes and vascular endothelial cells under stress conditions: a focus on mitochondrial quality control. *Oxidative Medicine and Cellular Longevity*, 2021, 2021.

[19] Mark L Dreher. Whole fruits and fruit fiber emerging health effects. *Nutrients*, 10(12):1833, 2018.

[20] Masoumeh Kordi, Fatemeh Aghaei Meybodi, Fatemeh Tara, Farzaneh Rashidi Fakari, Mohsen Nemati, and Mohammadtaghi Shakeri. Effect of dates in late pregnancy on

the duration of labor in nulliparous women. *Iranian journal of nursing and midwifery research*, 22(5):383–387, 2017.

[21] Fabio Sporchia, Nicoletta Patrizi, and Federico Maria Pulselli. Date fruit production and consumption: A perspective on global trends and drivers from a multidimensional footprint assessment. *Sustainability*, 15(5):4358, 2023.

[22] https://misbar.com/qna/2023/06/05/

[23] https://kouroshfoods.com/articles/dates-production-by-country-a-brief-guideline/.

[24] Pariwat Ongsulee. Artificial intelligence, machine learning and deep learning. In *2017 15th international conference on ICT and knowledge engineering (ICT&KE)*, pages 1–6. IEEE, 2017.

[25] Patrick O Glauner. Deep convolutional neural networks for smile recognition. *arXiv preprint arXiv:1508.06535*, 2015.

[26] Hyun Ah Song and Soo-Young Lee. Hierarchical representation using nmf. In *Neural Information Processing: 20th International Conference, ICONIP 2013, Daegu, Korea, November 3-7, 2013. Proceedings, Part I 20*, pages 466–473. Springer, 2013.

[27] A Saranya and R Subhashini. A systematic review of explainable artificial intelligence models and applications: Recent developments and future trends. *Decision analytics journal*, page 100230, 2023.

[28] S Agatonovic-Kustrin and Rosemary Beresford. Basic concepts of artificial neural network (ann) modeling and its application in pharmaceutical research. *Journal of pharmaceutical and biomedical analysis*, 22(5):717–727, 2000.

[29] Nariman Valizadeh, Majid Mirzaei, Mohammed Falah Allawi, Haitham Abdulmohsin Afan, Nuruol Syuhadaa Mohd, Aini Hussain, and Ahmed El-Shafie. Artificial intelligence and geo-statistical models for stream-flow forecasting in ungauged stations: state of the art. *Natural Hazards*, 86:1377–1392, 2017.

[30] David H Hubel and Torsten N Wiesel. Receptive fields and functional architecture of monkey striate cortex. *The Journal of physiology*, 195(1):215–243, 1968.

[31] Kunihiko Fukushima. Neocognitron: A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position. *Biological cybernetics*, 36(4):193–202, 1980.

[32] Rikiya Yamashita, Mizuho Nishio, Richard Kinh Gian Do, and Kaori Togashi. Convolutional neural networks: an overview and application in radiology. *Insights into imaging*, 9:611–629, 2018.

[33] Farhana Sultana, Abu Sufian, and Paramartha Dutta. Advancements in image classification using convolutional neural network. In *2018 Fourth International Conference on Research in Computational Intelligence and Communication Networks (ICRCICN)*, pages 122–129. IEEE, 2018.

[34] H Reynolds Anh. Convolutional neural networks (cnns). *Anh H. Reynolds*, 15, 2017.

[35] Maarouf Korichi, Marwa Mahcene, and Hadjer Bettayeb. *Brain Tumor Detection Using Deep Learning*. PhD thesis, University Of Kasdi Merbah Ouargla.

[36] Naveed Iqbal, Abdulmajid Lawal, and Azzedine Zerguine. Mitigating wireless channel impairments in seismic data transmission using deep neural networks. *Sensors*, 21(18):6105, 2021.

[37] Ning Qian. On the momentum term in gradient descent learning algorithms. *Neural networks*, 12(1):145–151, 1999.

[38] Sebastian Ruder. An overview of gradient descent optimization algorithms. *arXiv preprint arXiv:1609.04747*, 2016.

[39] Hamed Habibi Aghdam, Elnaz Jahani Heravi, Hamed Habibi Aghdam, and Elnaz Jahani Heravi. Convolutional neural networks, 2017.

[40] Andrew G Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, and Hartwig Adam. Mobilenets: Efficient convolutional neural networks for mobile vision applications. *arXiv preprint arXiv:1704.04861*, 2017.

[41] Sirawan Phiphiphatphaisit and Olarik Surinta. Food image classification with improved mobilenet architecture and data augmentation. In *Proceedings of the 3rd International Conference on Information Science and Systems*, pages 51–56, 2020.

[42] Junyi Chai, Hao Zeng, Anming Li, and Eric WT Ngai. Deep learning in computer vision: A critical review of emerging techniques and application scenarios. *Machine Learning with Applications*, 6:100134, 2021.

[43] Kirti Saini and Reeta Devi. A systematic scoping review of the analysis of covid-19 disease using chest x-ray images with deep learning models. *J. Auton. Intell*, 7(10.32629), 2023.

[44] Mark Sandler, Andrew Howard, Menglong Zhu, Andrey Zhmoginov, and Liang-Chieh Chen. Mobilenetv2: Inverted residuals and linear bottlenecks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 4510–4520, 2018.

[45] Dangfeng Pang, Zhiwei Guan, Tao Luo, Wei Su, and Ruzhen Dou. Real-time detection of road manhole covers with a deep learning model. *Scientific reports*, 13(1):16479, 2023.

[46] Niyazi Ari and Makhamadsulton Ustazhanov. Matplotlib in python. In *2014 11th International Conference on Electronics, Computer and Computation (ICECCO)*, pages 1–6. IEEE, 2014.

[47] Wes McKinney. Data structures for statistical computing in python. *Proceedings of the 9th Python in Science Conference*, pages 51 – 56, 2010.

[48] Hamdi Altaheri, Mansour Alsulaiman, and Ghulam Muhammad. Date fruit classification for robotic harvesting in a natural environment using deep learning. *IEEE Access*, 7:117115–117133, 2019.

[49] Amin Nasiri, Amin Taheri-Garavand, and Yu-Dong Zhang. Image-based deep learning automated sorting of date fruit. *Postharvest biology and technology*, 153:133–141, 2019.

[50] Hamdi Altaheri, Mansour Alsulaiman, and Ghulam Muhammad. Date fruit classification for robotic harvesting in a natural environment using deep learning. *IEEE Access*, 7:117115–117133, 2019.

[51] Aiman Al-Sabaawi, Reem Ibrahim Hasan, Mohammed A Fadhel, Omran Al-Shamma, and Laith Alzubaidi. Employment of pre-trained deep learning models for date classification: A comparative study. In *International Conference on Intelligent Systems Design and Applications*, pages 181–189. Springer, 2020.

[52] Md Sakibul Hasan, Abdus Sattar, et al. Arabian date classification using cnn algorithm with various pre-trained models. In *2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV)*, pages 1431–1436. IEEE, 2021.

[53] Khaled Marji Alresheedi, Suliman Aladhadh, Rehan Ullah Khan, and Ali Mustafa Qamar. Dates fruit recognition: From classical fusion to deep learning. *Computer Systems Science & Engineering*, 40(1), 2022.

[54] Amjad Alsirhani, Muhammad Hameed Siddiqi, Ayman Mohamed Mostafa, Mohamed Ezz, and Alshimaa Abdelraof Mahmoud. A novel classification model of date fruit dataset using deep transfer learning. *Electronics*, 12(3):665, 2023.

[55] Abdulhamid Haidar, Haiwei Dong, and Nikolaos Mavridis. Image-based date fruit classification. In *2012 IV International Congress on Ultra Modern Telecommunications and Control Systems*, pages 357–363. IEEE, 2012.

[56] Murat Koklu, Ramazan Kursun, Yavuz Selim Taspinar, and Ilkay Cinar. Classification of date fruits into genetic varieties using image analysis. *Mathematical Problems in Engineering*, 2021(1):4793293, 2021.

[57] Aurangzeb Magsi, J Ahmed Mahar, Shahid Hussain Danwar, et al. Date fruit recognition using feature extraction techniques and deep convolutional neural network. *Indian Journal of Science and Technology*, 12(32):1–12, 2019.