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Title:

Local Binary Pattern (LBP) and its derivations for image classification

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Dedication

Dear Mom and Dad, I cannot thank you enough for all the support and love you've given me. I never would have made it here without you. Thank you for everything!

To my dear brothers and sister to all my friends to all those who were giving me any kind of support, a sincere smile.

Baha Eddine & Laid

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Abstract

Local Binary Pattern (LBP) has emerged in the early 1990s as one of the most prominent texture descriptors. Over the past two decades, a large number of different LBP variants have been proposed. The original LBP model has been modified on several levels in different ways. Many variants have been proposing in literature, such as uniform LBP on the level of grouping or elliptical LBP (ELBP) on the level of topology, etc.

This thesis is an analytical and comparative study of a variety of different LBP variants in order to reach experimental results that help us to better understand each variant from the studied variants and to determine the appropriate application for each one in the field of image classification based on the texture property.

At the beginning of the study, we discussed the original LBP descriptor proposed in 1994. We conducted the classification on four known databases: (Outex, DTD, Brodatz, Vistex). In order to achieve more classification results for different comparisons, we used two common types of classifiers (SVM, KNN). After that, the scope of the study was expanded to include 12 different variants of the original LBP. This thesis has been backed-up with a deep statistical analysis of the obtained results.

Keywords: Texture classification, local binary pattern, the variant LBP, SVM, KNN.

الملخص:

ظهرت ال (LBP) في بدايات التسعينات من القرن الماضي كواحدة من ابرز واصفات الملمس (texture descriptors) وفي خلال العقدين الاخيرين تم اقتراح عدد كبير من المتفريعات المختلفة لها حيث تم التعديل النموذج الاصلي ل LBP على عدة مستويات وبعدة طرق سواء على مستوى الترميز أو التجميع (grouping) مثل uniform LBP او على مستوى الشكل (topology) مثل elliptical LBP .

هذه الاطروحة هي عبارة عن دراسة تحليلية ومقارنتية لمجموعة من مختلفة تفريعات ال LBP بهدف الوصول الى نتائج تجربية تساعدنا في فهم افضل لكل تفريع من التفريعات التي شملتها الدراسة ,ومعرفة ماهي حالة التطبيق المناسبة لكل تفريع في ما يتعلق بمجال تصنيف الصور بناء على خاصية الملمس (texture) .

تطرقنا في بداية الدراسة الى تفريع ال LBP الاصلي الذي تم اقتراحه سنة في تسعينيات القرن الماضي، قمنا باجراء عمليات التصنيف على اربعة قواعد بيانات معروفة (Brodatz , Vistex , Outex ,DTD) و من اجل استخراج نتائج تصنيف اكثر لاجراء مقارنات مختلقة قمنا بإستخدام نوعين شائعين من المصنفات (SVM,KNN) .

بعد ذلك تم توسيع مدى الدراسة لتشمل 12 تفريع مختلف ل LBP الاصلي , استخرجنا نتائج التصنيف لكل تفريع وقمنا بعد ذلك بوضع النتائج ضمن جداول من اجراء المقارانات اللازمة .

الكلمات المفتاحية: Texture classification, local binary pattern, the variant LBP, SVM, KNN

Résumé

Le modèle binaire local (LBP) est apparu au début des années 1990 comme l'un des principaux descripteurs de texture. Au cours des deux dernières décennies, un grand nombre de variantes LBP différentes ont été proposées. Le modèle LBP original a été modifié à plusieurs niveaux de différentes manières. De nombreuses variantes ont été proposées dans la littérature, telles que LBP uniforme au niveau du groupement ou LBP elliptique (ELBP) au niveau de la topologie, etc.

Cette thèse est une étude analytique et comparative de différentes variantes de LBP afin d'atteindre des résultats expérimentaux qui nous aident à mieux comprendre chaque variante des variantes étudiées et de déterminer l'application appropriée pour chacun dans le domaine de la classification d'image basée sur la propriété de texture.

Au début de l'étude, nous avons discuté du descripteur original de la lombalgie proposée en 1994. Nous avons effectué la classification sur quatre bases de données connues : (Outex, DTD, Brodatz, Vistex). Afin d'obtenir plus de résultats de classification pour différentes comparaisons, nous avons utilisé deux types communs de classificateurs (SVM, KNN). Après cela, la portée de l'étude a été élargie pour inclure 12 variantes différentes de la LBP originale. Cette thèse a été sauvegardée avec une analyse statistique approfondie des résultats obtenus.

Table of Contents

List of Figures

List of Table

Chapter I:

General introduction

General Introduction:

Recently, with the advances in various multimedia technologies and of the intense use of digital cameras, large image databases are being created by scientific, educational, medical, industrial and other applications. These large volumes of images make difficult for a user to browse through the entire database. Besides, in many areas, the use of image analysis has increased.

Faced with this situation, the ability to classify images into semantic categories and objects (e.g. humans, mountains, animals, airplanes) is essential in order to manage and organize image collection.

Image classification is a very important step in the recognition task. It has map application fields as identification of wood images, recognition of faces, speech, fingerprints, etc. It has been a topic of intensive research in recent years.

What is a digital image?

Images manipulated by a computer are called digital images which are represented by a series of bits). The surface of a digital image is divided into a fixed size of elements called cells or pixels. Each pixel has a gray-level color taken at the corresponding location in the actual image.

The digitization of an image results from its conversion from the analogy state (continuous distribution of light intensities in a plane x * y) to a digital image. This digital image is represented by two or more-dimensional matrixes of numerical values X (x, y) where: x, y are the Cartesian coordinates of a point in the image, and X (x, y) is the gray-level or the color at this point.

I.1. Characteristics of a Digital Image:

The image is a structured set of data characterized by the following parameters:

I.1.1. Pixel:

Pixel corresponds to "Picture Elements" which is the smallest component of images. It is a computable entity which can receive a structure and quantification. If the bit is the smallest unit of information that can be processed by a computer, the pixel is the smallest element that can be manipulated by a display and print hardware or software.

I.1.2. Resolution:

Image resolution is defined by the number of pixels per unit length. The higher is the number of pixels per unit length of the image to be digitized, the greater the amount of information that describes the image and the higher the resolution (and the higher the image size). The size of a digital image can be defined as the result of multiplying the number of columns by the number of rows.

I.1.3. Luminance:

Luminance is the brightness degree of pixels. Good luminance is characterized by……

1. Bright images;

2. Good contrast: images where the range of contrast tends to white or black; cause loss of detail in dark or bright areas.

3. The absence of noise.

I.1.4. Color space: An image is composed of pixels that can usually be represented as a point in a 3- color space. The most known are: RGB (Red, Green, Blue), HSV*(*Hue, Saturation, Value).

a. RGB: The most commonly used model for representing colors is the RGB model (Red - Green - Blue), which is the model of the three basic colors. It associates with each color three components (or channels), that correspond to the respective intensities of three primary colors of the synthetic synthesis. The white corresponds to the maximum value for each channel, while the black corresponds to the three null components. It is an additive color model: the lights red, green, and blue are combined to create other colors.

The RGB color model can be visualized in the form of a cube, as illustrated in Figure 1:

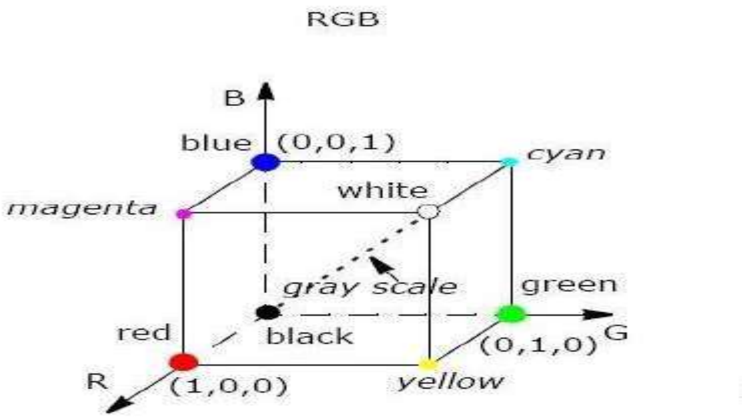


Figure 1. RGB Coordinate system.

b. HSV: The system (Hue - Saturation - Value) is defined by a cylinder that represents the hue, saturation, and value of a color. Hue H is represented by an angle between 0 and 360° which indicates the color family (red, yellow, green, blue, etc.). Saturation S gives information on the purity of the color. The value V corresponds to the luminous intensity.

It indicates whether the color is light or dark. Figure. 2.

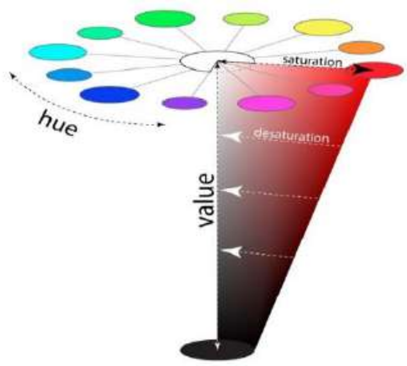


Figure 2. Hue, saturation, and the value
(brightness/luminosity) represented on a wheel of colors**.**

I.2. Image features:

Image features could be broadly categorized into three main categories which are color, texture and shape features. At first, they were widely used in image retrieval and then the same features were also used in image classification. Visual features of images present a description of its content.

I.2.1. Color features:

The Color is one of the most important features used for describing images. A color histogram is used for the most part as a popular method for representing the color feature.

Histogram:

A color histogram is a method for describing the color content of an image. it counts the appearance frequency of all color in the image [2]. The color histogram of an image is a rotation, translation, and scale invariant [1]. The color histogram can be extracted using some gray-level map of the image or the original color map.

Figure 3 shows an example of an image:

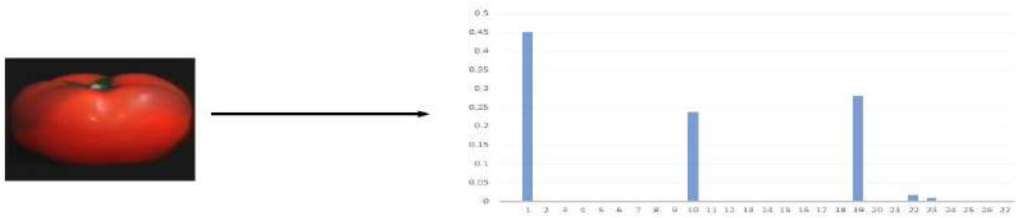


Figure 3: Color histogram for tomato image.

I.2.2. Shape features:

Shape attributes are often complementary to the color description. Shape attributes are used to characterize objects in images. There are two categories of shape descriptors: region-based descriptors and boundary-based descriptors. The first is used to characterize the entire shape of a region, the second relates to the characterization of the contours of the shape.

Figure 4 shows an example of a hand shape image:

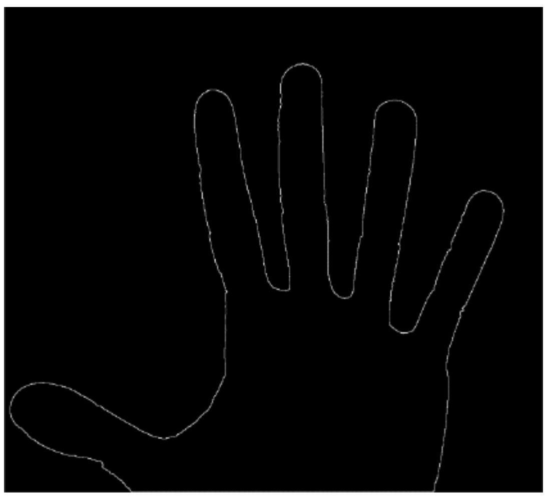
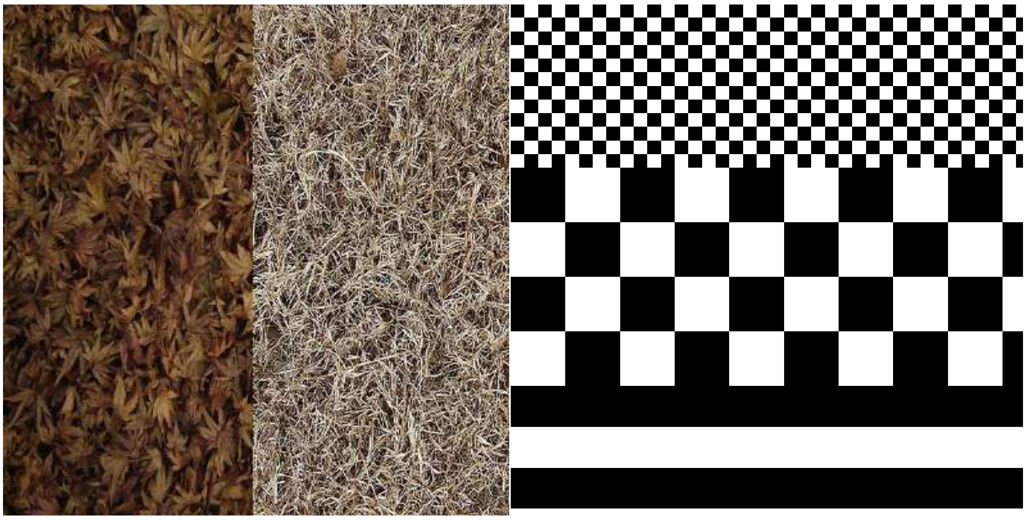


Figure 4: Example of a hand shape image.

I.2.3. Texture features:

There is no formula definition of texture. Generally, we can say that texture refers to the visual patterns that have properties of homogeneity and do not result from the presence of only a single color or intensity [3]. Typical examples of natural texture could be found in clouds, trees, bricks, grass, etc. Texture remains a poorly defined concept [4].
Many texture features have been introduced in literature such as GLCM [5], LBP [6], BSIF [7], etc.

Figure 2 shows an example of two types of texture.



(a) (b)

Figure 5: Example of two types of texture, (a) natural texture and (b) artificial texture.

Several approaches have been proposed to represent texture. We mention the three most known ones which are statistical, frequency and geometrical.

I.2.3.1 Statistical methods:

Statistical methods consist in calculating the appearance frequency different gray-levels in the image, then they derive some statistical moments (such as correlation, energy, etc.) from these often appearing histograms.

a. Co-occurrence Matrices:

Gray-Level Co-occurrence Matrix (GLCM) [5] is generated by calculating the frequency number of gray-level pairs within a texture image, also known as the gray-level spatial dependence matrix. GLCM calculate the statistical features based on gray level intensities of the image. These features of the GLCM are used in texture recognition, image classification, image retrieval, color image analysis, object recognition and texture analysis methods and image segmentation, etc.

b. Local binary Pattern:

Local Binary Pattern (LBP) [6] is a simple texture operator, has proven its ability as a powerful feature in many applications including texture classification and segmentation. The basic LBP operator is computed by assigning each pixel within the image to a binary code of eight bits. This code is computed by thresholding the 3 x 3 neighborhood of each pixel and considers the result as a binary number.More details will be given in Chapter III about this approach of representation. We will introduce the LBP operator and its different variants of details.

I.2.3.2. Frequency Methods:

Frequency-based methods define the image as a set of signals with amplitudes and directions. These methods consist of extracting the energy carried by signals in different frequency bands. One of many frequencies based method is Gabor filters [8, 9].

Figure 5 shows an example of real image and Fourier transform image:

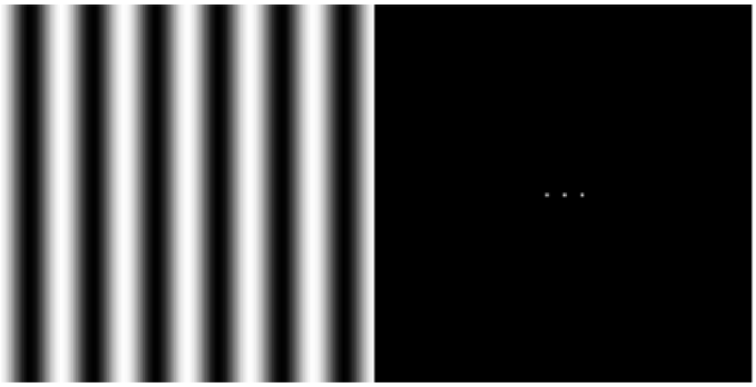


Figure 6: Real image and Fourier transform image.

I.2.3.3. Geometrical Methods:

Geometrical-based methods used for structural analyze of a texture to identify the primitive motif that constitutes a texture and the rule it follows in its distribution.

I.3. Problematic &Solution:

Texture is a fundamental characteristic of the appearance of all surfaces from objects around us, and it represents a significant part of digital images, which makes it a key component of many computer vision systems. Texture classification is one of the major problems when dealing with texture study, so it has received large attention due to its usefulness to understanding how humans recognize textures as well as its important role in the fields of computer vision and pattern recognition, and that includes biomedical image analysis, object recognition, biometrics and many other fields [10].

One of many methods to study textures classification is Local Binary Patterns (LBP) which emerged as one of the most popular and extensively studied local texture descriptors. However, many LBP variants has been proposed, to the point that it can become difficult to follow their respective strengths and weaknesses, so it becomes clear that we are in need for comparative studies regarding the many LBP-related strategies. In this work, we aim at explaining the basic form of the LBP operator. Some recent and popular variants of LBP are reviewed and thoroughly discussed afterward. A comparative study of variables is conducted by testing them on a set of texture database Known (Outex [11], Brodatz [12], Vistex [13], DTD [14]) and classifiers (SVM [15], KNN), after the analysis, the best couple (Descriptor, Classifier) is chosen.

I.4. Thesis organization:

Chapter II: Classification methods

We introduce explanations about the two main classification approaches which are: Supervised and Unsupervised learning. And the definition of some classification algorithms used in our study (KNN, SVM).

Chapter III: the variant LBP

We provided an illustration of the basic form of the LBP operator in addition to some of its recent and most popular variants.

Chapter IV: Experimental Results

The fourth chapter contains a description of the different experiments carried out and the analysis of the results obtained. We presented comparative results with different descriptors and classifiers and analyzed the performance in order to find the best couple (LBP variant, classifier) for the job.

Finally, the thesis is finished by a general conclusion where we summarized the main results obtained.

Chapter II:

Classification Methods

II.1. Introduction:

The intent of classification process is to categorize an image into one of several classes. It is used two main classification methods are Supervised and Unsupervised learning. In this chapter, we will give a concept of classification with an explanation of the two methods (Supervised and Unsupervised).

What is the classification?

A Classification is a discipline related closely or from afar to several domains, it is also known under various names (classification, clustering, segmentation, etc.) according to the objects it deals with and the objectives it aims to achieve. Image classification is a particular case of Pattern Recognition. The overall objective of the classification process is to automatically classify some unknown image into one or more known classes. As a training step, the classifier is provided by a well-annotated dataset. As a test step, an unlabeled image is given to the trained classifier aiming to map it to the right category. The are two main classification approaches which are: Supervised and Unsupervised learning.

Image classification may be carried out using the annotation or the contents of the image.

II.2. Supervised classification:

A supervised algorithm analyses the training data and produces an inferred function which can be used for mapping new examples. In this approach, the training dataset is well labeled which means that the data are already assigned to a set of pre-defined classes (training set). The aims to determine the class (label) of a new data.

There are many supervised learning algorithms such as k-nearest neighbors (KNN), Support Vector Machines (SVM) [15], Naive Bayes classifier … etc.

II.2.1. KNN(k-Nearest-Neighbors):

K-nearest neighbor (KNN Fix and Hodges, 1951) algorithm is among the simplest of all machine learning algorithms. Is a supervised classification method, which stores all available data (training set) and classifies new data based on the similarity measure.

We can summarize the algorithm's steps as follows:

1. Determine the value of the variable k, which expresses the number of neighbors.

2. We calculate the distance between the new example and the examples in the dataset.

3. we arrange examples to get the neighbors depending on the least distance calculated in the previous step and take them the number of adjacent k.

4. we define the class for the neighbors.

5. The most common class of neighbors is the expected class.

Figure 7 shows visualize the process of KNN classification.

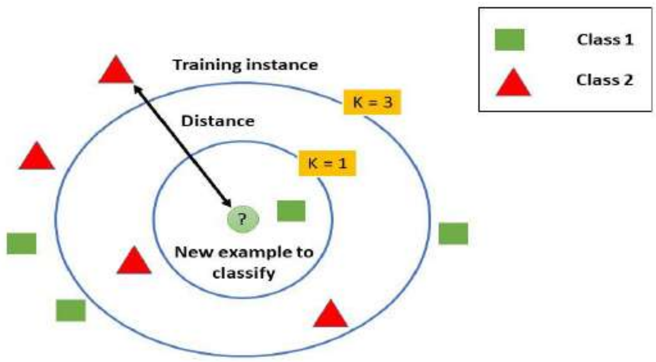


Figure 7: KNN Classification.

A distance between objects. It can be measured with different distance functions:

Euclidean distance: $\left(\sum_{i=1}^{n}(xi-yi)^2\right)^{\mathbf{1/2}}$ (1)

Manhattan distance: $\sum_{i=1}^{n} |xi - yi|$ (2)

Minkowski distance: $\sqrt[p]{\sum_{i=1}^{n} |xi - yi|^p}$ (3)

Where (Xi, Yi) represent the coordinates of the data point.

II.2.2. Support vector machine (SVM):

The Support Vector Machine (SVM) It was first proposed by Vladimir N. Vapnikin 1995 In his work on structural risk minimization. SVM is supervised learning classifier based on statistical learning theory [15].

SVM is an algorithm popular using in many pattern recognition problems in recent years, including texture classification [16].

Support Vector Machines were first introduced to solve the pattern classification and regression problems. It was initially designed for binary separation problems [15].

In SVM, a data point is viewed as an n-dimensional vector, in n-dimensional space R^n and we want to know whether we can separate such points with an (n-1) dimensional hyperplane (Canonical plane). This is called a linear classifier [17].

The figure below illustrates the principle of SVM algorithm:

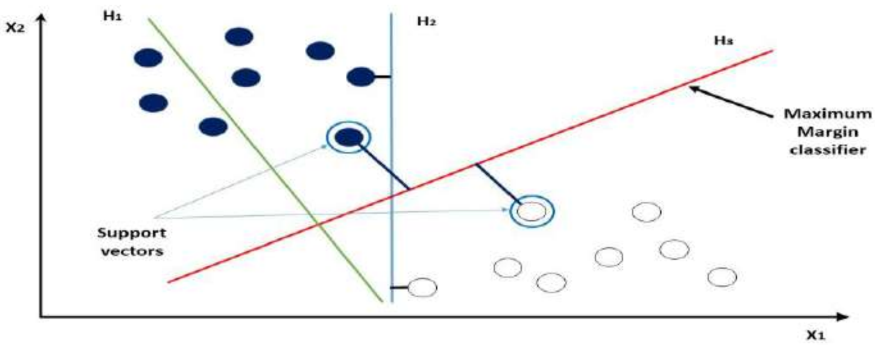


Figure 8: SVM algorithm principal.

All points that are located on the border are named support vectors.

If the classes are not separated in linearly, SVM finds hyperplane to increase the maximum margin and at the same time tries minimizing a quantity proportional to the number of misclassification errors. Concerning the trade-off between margin and misclassification error is controlled by a user-defined constant [15].

To classify a non-linear dataset (in the case of no-linearly separable data), the input data is mapped to another high dimensional feature space where the data is linearly separable (Figure 8).

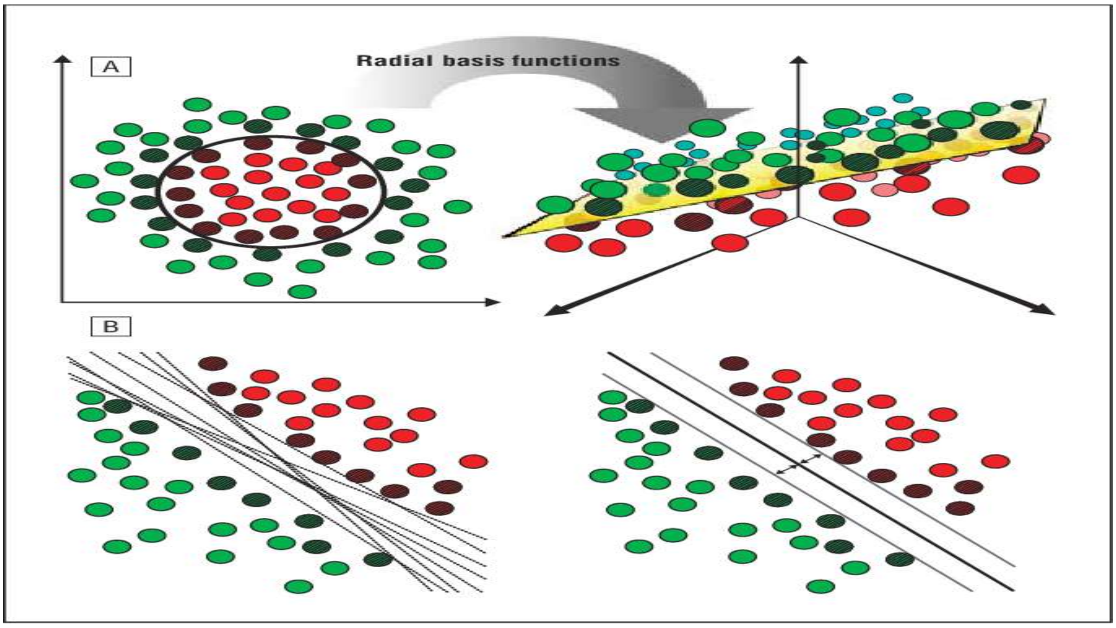


Figure 9: Nonlinear classification using SVM

Presently there are two types of approaches for multi-class SVM [17]:

1. By building and collect several binary classifiers: In this approach, several methods have been proposed such as one-against-all, one-against-one, and DAGSVM methods.
2. By directly considering all data in one optimization formulation.

II.2.3 Naive Bayes classifiers:

Naive Bayes classifier is a simple Statistical Bayesian Classifier. A naive Bayes classifier is an algorithm that uses Bayes' theorem to classify objects with a presumption of independence between predictors. It assumes that the presence of a certain feature in a class is unrelated to the presence of any other feature.

Bayes theorem is used for calculating the rear probability P(C|X), from P(C), P(X), and P(X|C).

$$\boldsymbol{P(C|X) = \frac{P(C)*P(X|C)}{P(X)}} \qquad (4)$$

Where:

P(C|X) is the posterior probability of class (target) given predictor (attribute).

P(C) is the prior probability of *class*.

P(X|C) is the likelihood which is the probability of *predictor* given *class*.

P(X) is the prior probability of predictor.

II.3. Unsupervised Learning (Clustering):

In this approach, the input data is unlabelled, there is no predefined dataset for training. The goal is to cluster similar input into logical groups.

The clustering engine goes through the input data completely and based on the characteristics of the data, it will decide under which cluster it should be grouped. Several clustering algorithms were proposed. Examples of well-known algorithms include K-means, Fc-means, etc. …

II.3.1. K-means:

K-means is one of the learning algorithms and that solve the well-known clustering problem. K-Means is a prototype-based simple partitional clustering technique. The algorithm classifies objects to a pre-defined number of clusters, which is given by the user (assume k clusters).

The steps of the K-means algorithm are the following:

a. Select initial centroid of the k clusters.
b. Calculate the distance between each point and center, using Euclidean distance.
c. Gather the data to its nearest center.
d. repeat steps b through c until the cluster membership stabilized.

II.3.2. FC-means:

FCM is a method of clustering which allows one piece of data to belong to two or more clusters, which was proposed by Dunn [18] in 1973 and eventually modified by Bezdek [19, 20] in 1981. is frequently used in many fields. This method is frequently used in pattern recognition.

It is based on minimization of the following objective function:

$$\boldsymbol{j_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^{m} \left|\left|x_i - c_j\right|\right|^2} \quad (5)$$

where,

m: Any real number greater than 1, it was set to 2.00 by Bezdek [].

u_{ij}: is a membership degree of x_i in the cluster j.

x_i: is the i^{th} of measured data.

c_j: is the center of the cluster, and || || is any norm that measured the similarity between data in the center cluster.

||*||: Any norm expressing the similarity between any measured data and the center.

II.4. Conclusion:

In this chapter we presented an introduction to the classification of images, then we addressed the concept of supervised and unsupervised and explained some known classification algorithms (KNN, SVM), with a simple concept of some clustering algorithms (K-means, Fc-means).

Chapter III:

The variants of Local binary patterns (LBP)

III.1. Introduction:

Amongst many methods, Local Binary Pattern (LBP) methods [6] have emerged as one of the most prominent and widely-studied classes of texture features, such that a vast number of LBP variants have been proposed for a diverse range of problems including texture classification. In this chapter, we explain the basic form of the LBP operator. Then, some recent and popular variants of LBP are reviewed and thoroughly discussed.

III.2. The variants of the Local binary patterns (LBP):

III.2.1. LBP

Introduced by Ojala et al. [6]. The original LBP operator describes the nearby areas of a pixel by generating a binary code of eight neighboring pixels. The LBP operator takes the 3-by-3 pixels patch that surrounds a central pixel. The positive values, which are obtained as result of subtracting the central from neighboring pixels, are then encoded with 1 and the negative with 0. All binary values for each pixel are then concatenated in a clockwise direction to obtain a binary number value beginning from the top-left neighbor. The binary number is then transformed to its decimal value. The obtained binary numbers values are called as LBP codes. The appearance frequency of each code, called pattern, in the image is then computed to construct a histogram of 256 (2^8) dimensions. Figure 9 shows the basic LBP operator:

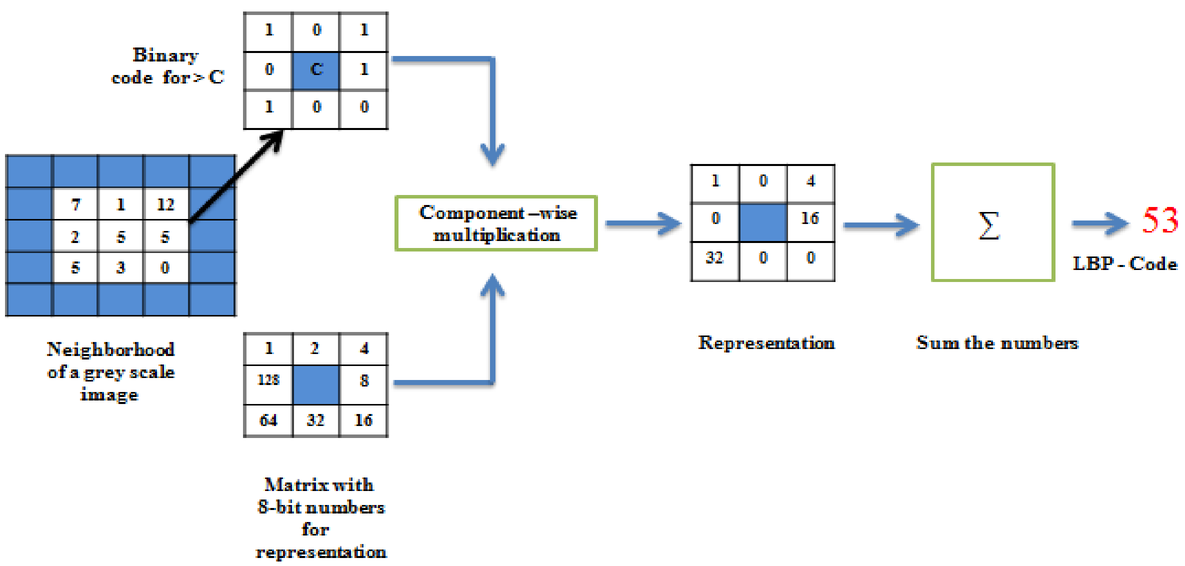


Figure 10: The operator LBP.

III.2.2. Uniform LBP:

We say that LBP is a uniform pattern. If it contains only two transitions from 0 to 1 or vice versa when the corresponding bit string is considered circular. For example, the patterns 00000000 (0 transitions), 01110000 (2 transitions) and 11001111 (2 transitions) are uniform, whereas the patterns 11001001 (4 transitions) and 01010011 (6 transitions) are not [21]. In case of uniform LBP mapping, there is a separate output label for each uniform pattern, and all the non-uniform patterns are assigned to a single label. Thus, the number of different output labels for mapping patterns of N bits is N(N–1) + 3. For instance, the number of labels with the neighborhood of 8 pixels is 256 for the standard LBP but only 59 for LBP Uniform. Figure 10 shows LBP Uniform.

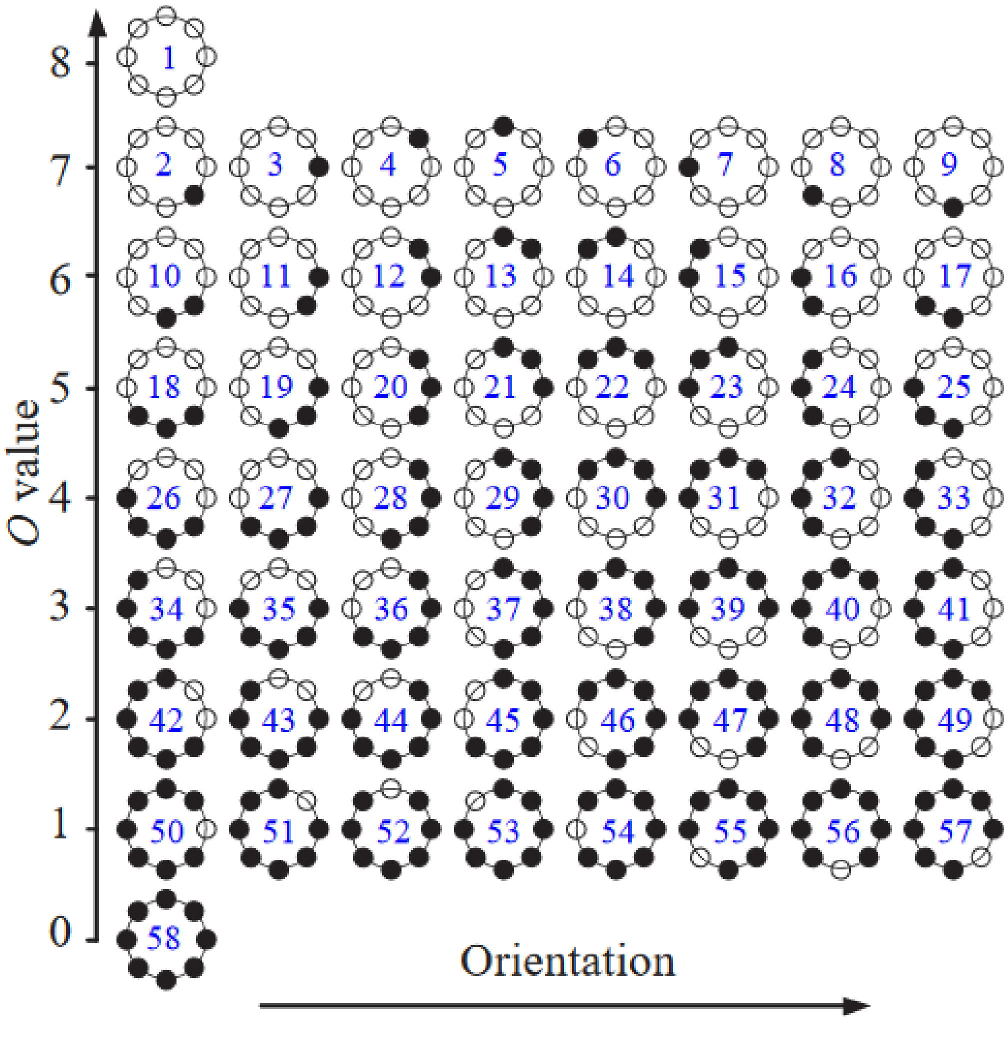


Figure 11: Uniform LBP.

III.2.3. LBP Rotational:

In rotational LBP [22] we group the binary patterns that have the same rotation into one group so we have in result only 36 possible binary patterns left as shown in figure 11 below.

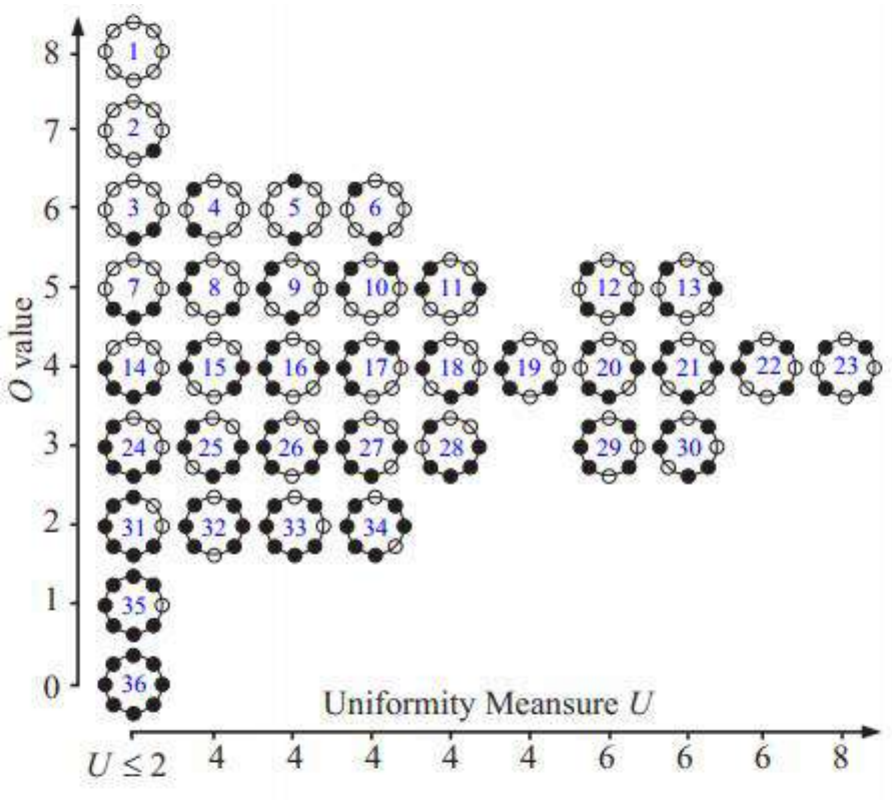


Figure 12: LBP Rotational.

III.2.4. Rotational Uniform Local Binary Pattern:

In the Rotational Uniform Local Binary Pattern [23], we group all the binary patterns that have more than < 2 Uniformity into one group so we have in result 10 groups possible as shown in figure 12 below.

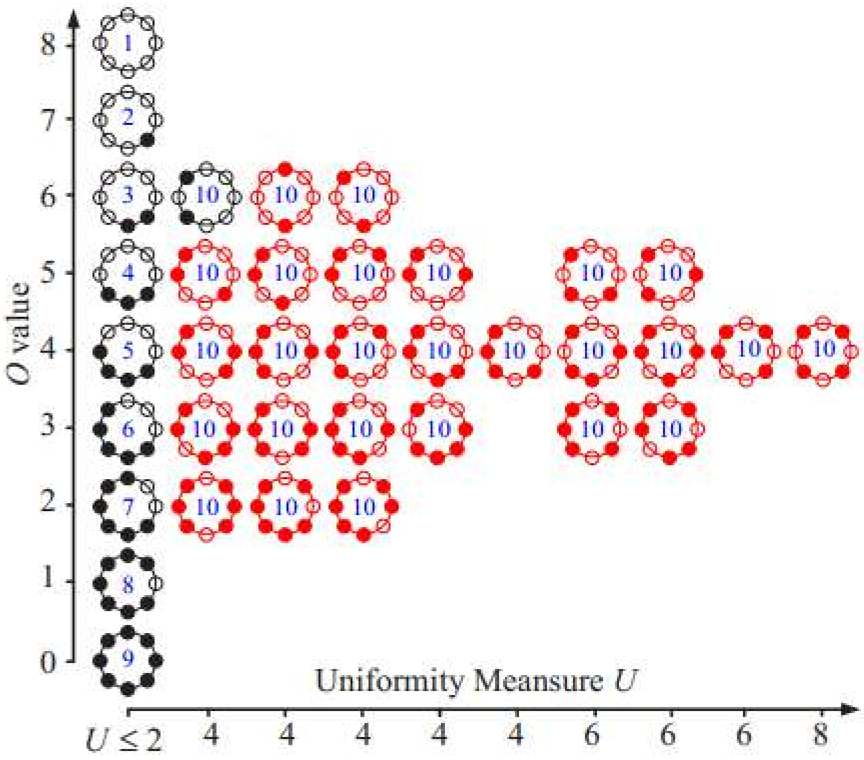


Figure 13: Rotational Uniform Local Binary Pattern.

III.2.5. Elliptical Local Binary Pattern (ELBP):

In ELBP [24], at each pixel (xc, yc), is the center. Is taken its neighboring pixels that lie on an ellipse (Figure 13. (c-d)). Is calculated ELBP of (xc, yc) with P surrounding pixels at (R1, R2) as follows:

$$ELBP^{P,R1,R2}(x_c, y_c) = \sum_{i=1}^{P} s(g_i^{P,R1,R2} - g_c)2^{i-1}$$

S(x) function is defined as Eq.

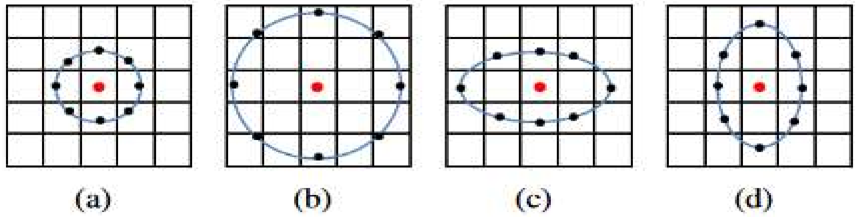


Fig. 1. $\mathbf{LBP^{8,1}}$, $\mathbf{LBP^{8,2}}$, $\mathbf{ELBP^{8,2,1}}$ and $\mathbf{ELBP^{8,1,2}}$ patterns.

Figure 14: ELBP.

III.2.6. Noise-Tolerant Local Binary Pattern:

NTLBP [25], is designed to work with images with a high level of noise, we take the grouping of patterns as shown in figure 14 below.

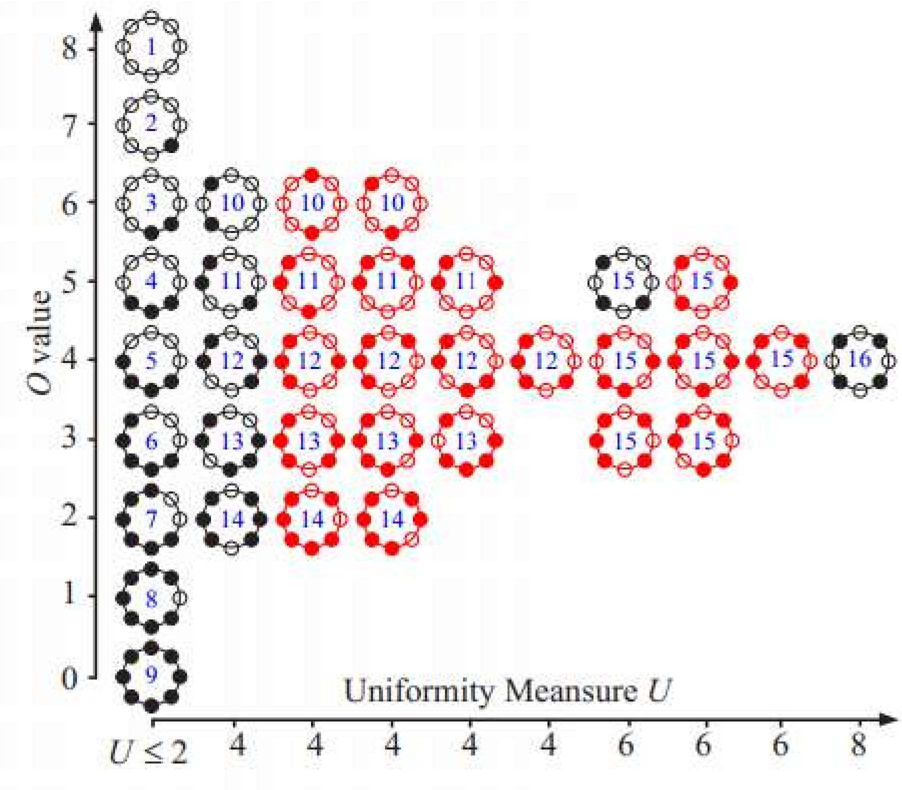


Figure 15: Noise-Tolerant Local Binary Pattern.

III.2.7. Sorted Local Binary Pattern:

In SLBP [26], we group the binary patterns according to the bit which has the value of 1 in the pattern.

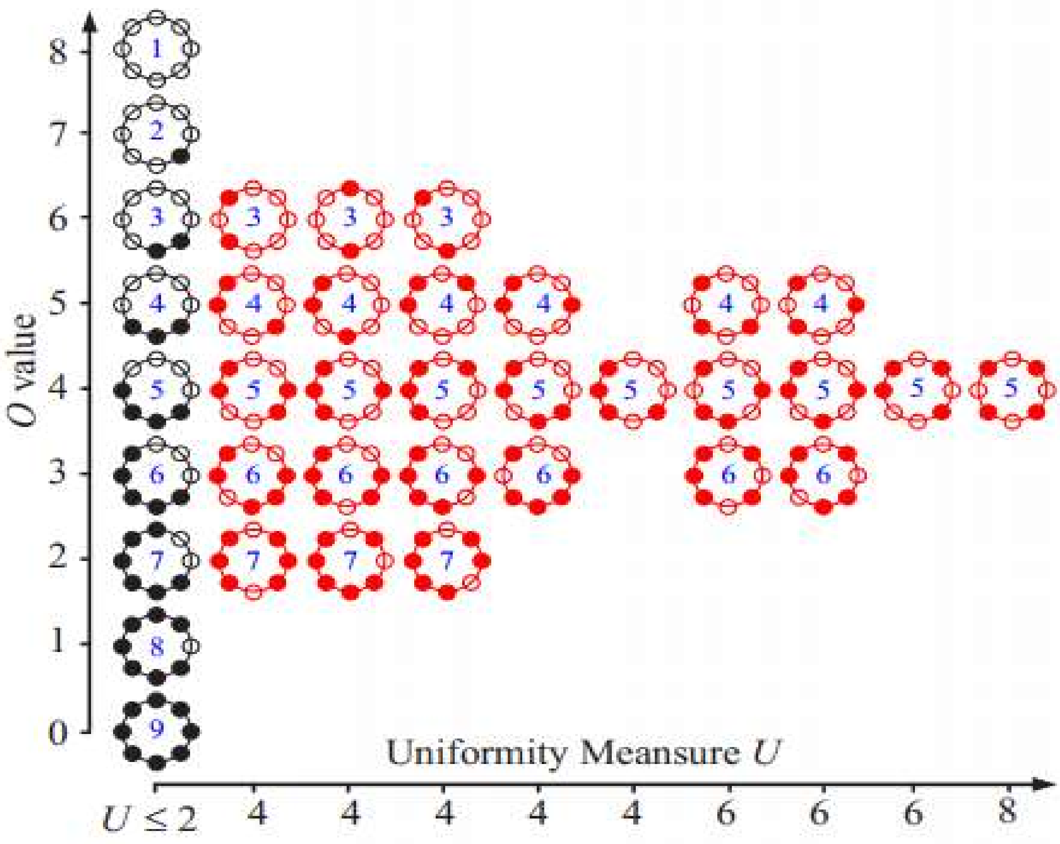


Figure 16: Sorted Local Binary Pattern.

III.2.8. Number Local Binary Pattern:

In the NLBP [27], the pattern is further divided into different groups based on the numbers of `1' bits and `0' bits. Show figure 16.

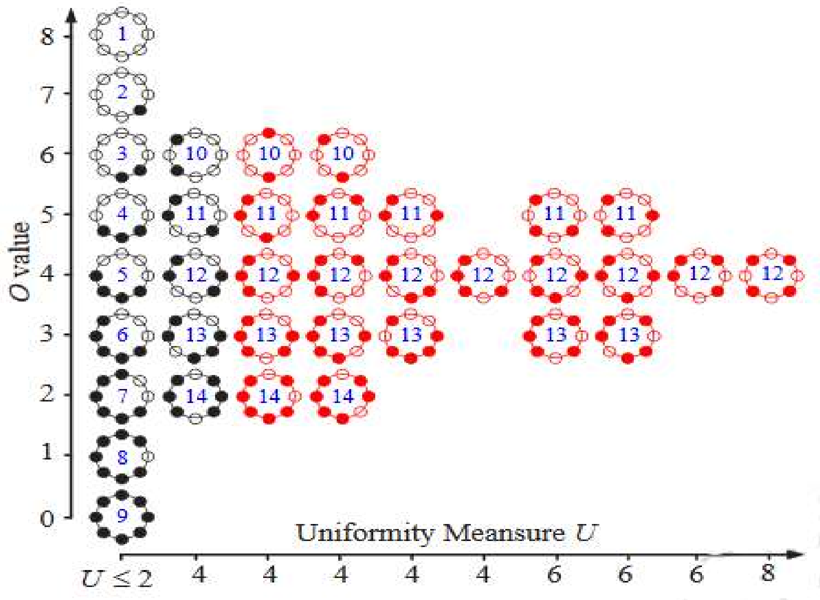


Figure 17: Number Local Binary Pattern.

III.2.9. Rotation, Symmetry, and Complement Invariant:

In the RSCILBP [28], we take all the symmetric pattern into the same grouping.

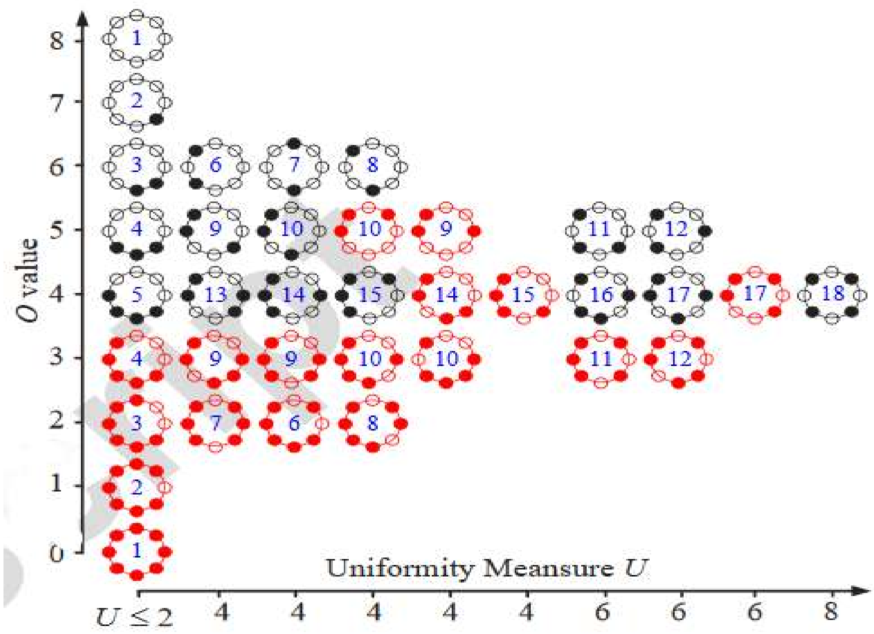


Figure 18: Rotation, Symmetry, and Complement Invariant

III.2.10. Novel Extended Local Binary Pattern:

NELBP [29], operator classifies and combines the “non-uniform” local patterns based on analyzing their structure and occurrence probability the grouping is shown in figure 18 below.

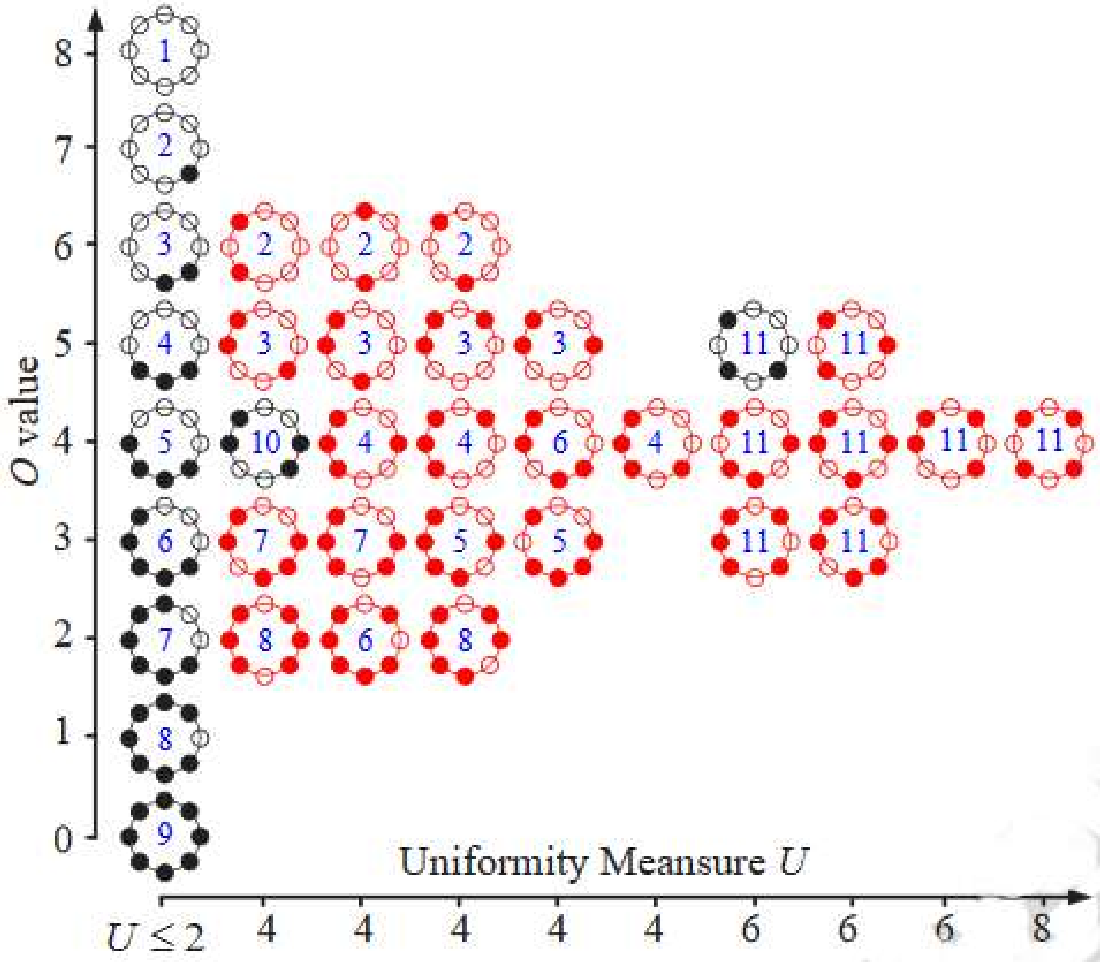


Figure 19: Novel Extended Local Binary Pattern

III.2.11. Dominant Local Binary Pattern:

The dominant local binary pattern (DLBP) [30], the method makes use of the most frequently occurred patterns to capture descriptive textual information. Show figure 19.

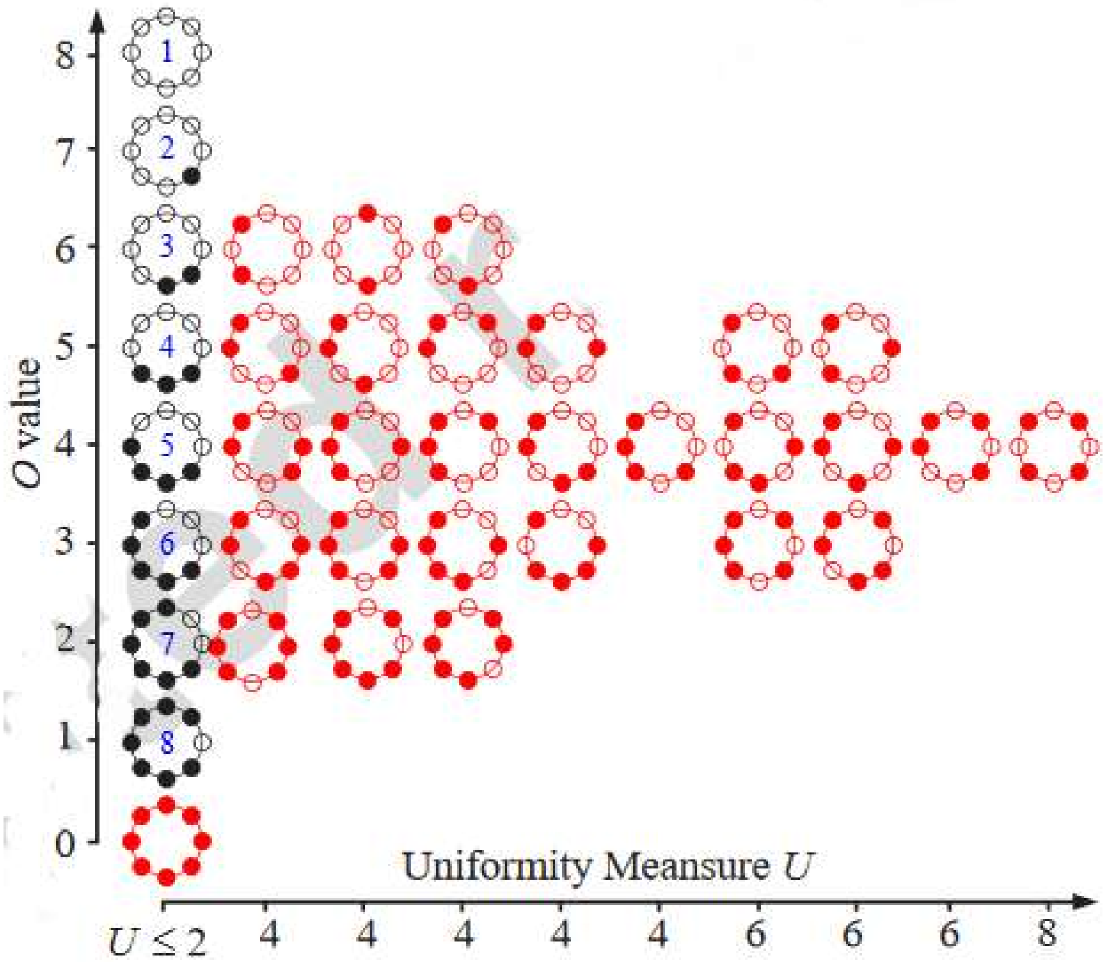


Figure 20: Dominant Local Binary Pattern

III.2.12. Discriminative Local Binary Pattern:

In Discriminative Local Binary Pattern [31], the pattern is learned discriminatively. the grouping of the binary pattern is shown in figure 20 below.

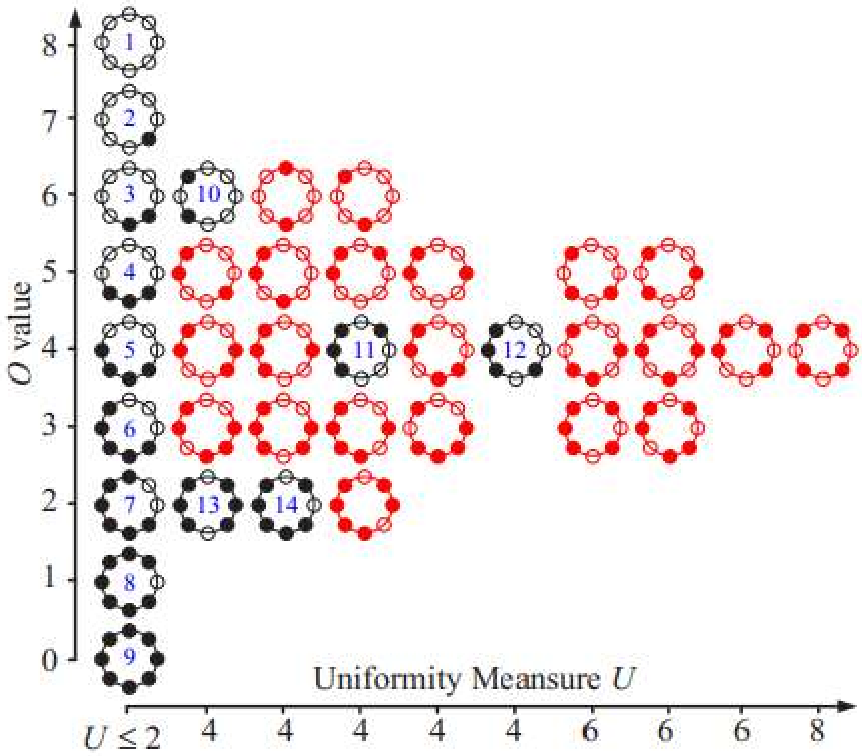


Figure 21: Discriminative Local Binary Pattern.

Table 1: Dimensionality comparison for LBP variants:

Methods	Dimension
LBP	256
LBP_R	36
LBP_U	59
LBP_RU	10
SLBP	9
ELBP	256
NELBP	11
NLBP	14
NTLBP	16
RSCILBP	18
DLBP	7
DisLBP	14

III.3. Conclusion:

In this chapter, we presented a detailed explanation of the LBP main operator, and we reviewed the recent and common 12 variants of the LBP that we used on in our study.

Chapter IV:

Experimental Results

IV.1. Introduction:

This chapter provides a comprehensive review of experimental results using of 12 LBP variants and some of the classifier methods used along with these LBP variants. To evaluate our Results several tests have been performed using on four known databases: (Outex, DTD, Brodatz, Vistex) and two types classifier algorithms (SVM, KNN).

IV.2. Experimental setup:

IV.2.1. Development tools:

We have used MATLAB, as an environment to construct our proposed system. The version used is MATLAB R2016a. There are many reasons, which explain our preference for this environment on the other environments:

- A very large database of built-in algorithms for image processing.
- MATLAB supports reading all of the popular image formats.
- MATLAB's functionality can be greatly expanded by the addition of toolboxes. These are sets of specific functions that provide more specialized functionality.
- Programming infinitely faster for calculation and display.
- MATLAB is supported on many different computer systems, providing a large measure of platform independence.
- MATLAB includes tools that allow a programmer to interactively construct a Graphical User Interface (GUI) for his or her program. With this capability, the programmer can design sophisticated data-analysis programs that can be operated by relatively inexperienced users.

This is concerning the software that we have used.

The test has been taken under Windows 10, Intel i3-4030U of processing power of 2 GHz CPU with 4GB of RAM.

IV.2.2. Database:

Numerous texture-dataset benchmarks have been proposed in literature such as Outex [11], Brodatz [12], Vistex [13], DTD [14], etc.

In our study, we used four texture-dataset benchmarks: Outex [11], Brodatz [12], Vistex [13], DTD [14] to perform our tests.

- **Outex:** There exist several releases of this dataset (The Center for Machine Vision and Signal Analysis (CMVS)). We choose Outex_TC_00000, Contains 24 textures. Database TC-00000 comprises 480 single-orientation texture images with a size of 128×128. Sample images of the OuTex textures are shown in Figure 22.

Figure 22: Samples of three images from the OuTex texture album.

- **Brodatz:** The Brodatz texture database [12], is an old and a standard texture database that contains grey-scale images. The Brodatz textures are popular and widely used in texture classification, It consists of 112 textures. Sample images of the Brodatz textures are shown in Figure 22.

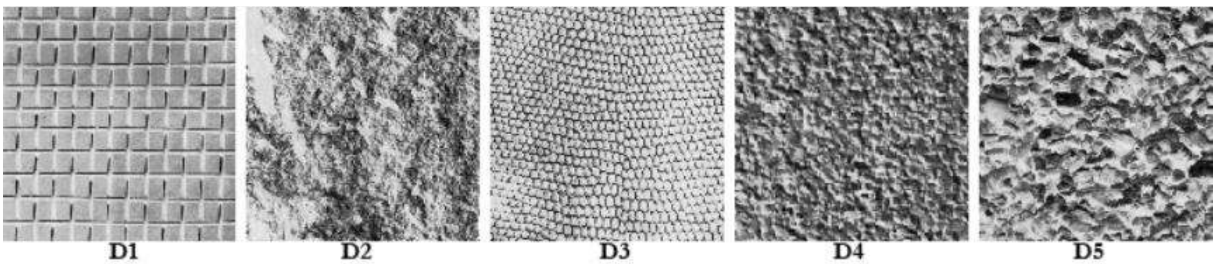


Figure 23: Samples of five images from the Brodatz texture album.

The Brodatz database (Brodatz, 1966), which is used in our study, consists of 14 texture images so that the image is divided into parts (64 x 64 images) as shown in Figure 23.

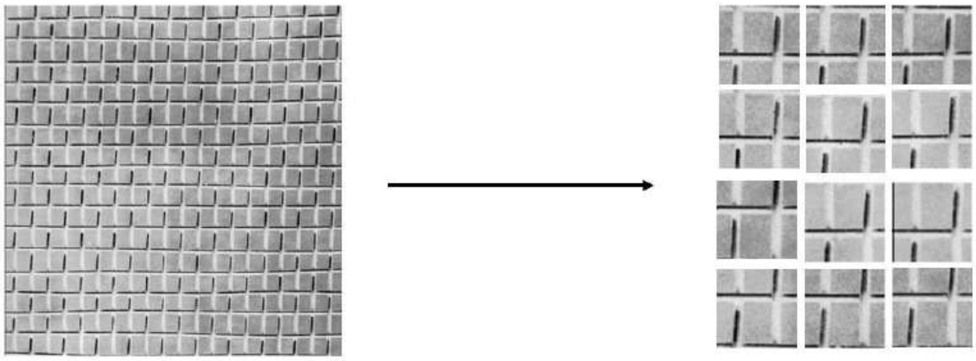


Figure 24: Sample image of the Brodatz texture divided into parts.

- **Vistex:** The Vision Texture Database (VisTex) [13]. Is a collection of texture images, built by the MIT Multimedia Lab. It has 19 classes of textures, each with a different number of images. The database was created with the intention of providing a large set of high-quality textures for computer vision applications. Figure 24 shows a representative sample.

Figure 25: Examples of three textures from the VisTex dataset.

- **DTD:** The Describable Textures Dataset (DTD) [14] is a texture database, contains 5640 images, Classified to 47 terms (categories). Each category consists of 120 images for each category. Image sizes range from 300 x 300 and 640 x 640.

Sample images of the DTD textures are shown in Figure 25.

Figure 26: Examples of fifteen textures from the DTD dataset.

Table 2: Summary of texture datasets used in our experiments.

Texture Dataset	Texture Classes	Sample Size (pixels)	Samples per Class	Training per Class	Testing per Class	Samples in Total	Train/Test Predefined?
Outex_TC00000	24	128 x 128	20	240	240	480	Yes
Brodatz	111	64 x 64	14	44	662	896	No
VisTex	167	512 x 512	17	97	17	114	No
DTD	47	523 x 480	11	990	220	1210	No

IV.3. Experimental Results:

In this section, we will present our results for the recognition of textures. We present comparative results with different descriptors and classifiers and analyze the performance in order to find the couple (LBP variant, classifier) best combination.

$$Performance = \frac{\boldsymbol{Recognized\ textures * 100}}{\boldsymbol{Total\ number\ of\ testing\ textures}}$$

IV.3.1. OuTex:

Table 3: Classification scores (%) for various methods on Outex-TC00000.

Test Suite	Outex-TC00000	
	Classifiers	
Methods	KNN	SVM
LBP	98.75	99.58
LBP_Uniform	98.75	99.58
LBP_R	93.33	95.41
LBP_Uniform_R	90.41	95
ELBP	99.16	99.58
SLBP	92.5	93.33
DLBP	88.75	91.67
NLBP	92.5	95
NELBP	90.83	94.16
NTLBP	92.5	95
RSCILBP	90.41	94.58
DisLBP	88.75	93.33

Based on these results, we can make the following conclusions:

- ELBP, LBP, and LBP_Uniform have the highest performance of any LBP variants. Moreover, they perform slightly better on SVM classifier.
- DisLBP and DLBP have the worst performance with below 90% recognition rate while used with KNN classifier. When used with SVM classifier, the recognition rate slightly improves and gets over 90%.
- Even though SVM classifier performed better than KNN classifier on all tests, KNN has competitive results with all LBP variants.

IV.3.2. VisTex:

Table 4: Classification scores (%) for various methods on VisTex.

Test Suite	VisTex	
Methods	Classifiers	
	KNN	SVM
LBP	36.84	36.84
LBP_Uniform	34.21	5.26
LBP_R	36.84	10.52
LBP_Uniform_R	34.21	13.15
ELBP	34.21	21.05
SLBP	34.21	13.15
DLBP	34.21	5.26
NLBP	36.84	13.15
NELBP	36.84	13.15
NTLBP	36.84	10.52
RSCILBP	34.21	5.26
DisLBP	34.21	5.26

Based on the results, we can make the following conclusions:

- KNN classifier has a clear advantage over SVM classifier in almost all tests, with the differences being very significant in LBP_R, DLBP, RSCILBP, and DisLBP.
- LBP is the unique case by having SVM and KNN perform similarly.
- With KNN classifier, all methods perform very similarly to each other.
- With SVM classifier, LBP stands out as the best method by having the highest recognition rate.

IV.3.3. Brodatz:

Table 5: Classification scores (%) for various methods on Brodatz.

Test Suite	Brodatz	
	Classifiers	
Methods	KNN	SVM
LBP	96.42	96.78
LBP_Uniform	91.07	95
LBP_R	81.78	88.21
LBP_Uniform_R	83.92	86.42
ELBP	96.78	97.14
SLBP	80	82.14
DLBP	80	85.35
NLBP	83.57	89.64
NELBP	81.42	87.14
NTLBP	82.5	88.92
RSCILBP	74.64	87.14
DisLBP	80	87.14

Based on the results, we can make the following conclusions:

- ELBP and LBP have the highest performance of any LBP variants. And they perform slightly better on SVM classier.
- RSCILBP with KNN classifier has the worst performance by having unreliable 74% recognition rate. However, when used with SVM classifier RSCILBP performs comparably to most other LBP variants.
- SVM classifier performed better than KNN classifier on all tests, with a clear advantage in most methods.

IV.3.4 DTD:

Table 6: Classification scores (%) for various methods on DTD.

Test Suite	DTD	
	Classifiers	
Methods	KNN	SVM
LBP	31.36	5.45
LBP_Uniform	28.18	11.81
LBP_R	33.63	13.63
LBP_Uniform_R	27.72	11.63
ELBP	35.45	11.36
SLBP	30.9	10.9
DLBP	30	6.36
NLBP	31.36	11.81
NELBP	33.18	14.09
NTLBP	29.54	7.72
RSCILBP	28.18	10
DisLBP	30.9	14.09

Based on the results, we can make the following observations:

- Just like in Vistex database, KNN classifier has the edge over SVM classifier in all tests, with the differences being very significant in LBP, NTLBP, DLBP, and DisLBP.
- ELBP with KNN has the highest performance of all methods. With LBP_R and NELBP right behind it in recognition rate.
- LBP with SVM classifier has the worst performance by having 5.45% recognition rate.

IV.4. Conclusion:

In this chapter, we provided a review of the total of 12 LBP variants and some of the classifier methods used along with these LBP variants. We performed evaluation tests for texture classification using these variants on four known databases: (Outex, DTD, Brodatz, Vistex), and as classifier methods, we used two common types of classifiers (SVM, KNN).

The results demonstrated what are strengths and limitations of each LBP variants, and we've seen good performance in the database Outex and Brodatz, but the results weren't as good with DTD and Vistex. We also notice also that the SVM classifier get a better performance than KNN in the case of the Outex and Brodatz Datasets but the KNN classifier performed better in the other two databases.

General conclusion:

Texture is a fundamental characteristic of the appearance of all surfaces from objects around us, and it represents a significant part of digital images, which makes it a key component of many computer vision systems. Texture classification is one of the major problems when dealing with texture study, so it has received large attention due to its usefulness to understanding how humans recognize textures as well as its important role in the fields of computer vision and pattern recognition, and that includes biomedical image analysis, object recognition, biometrics and many other fields.

One of many methods to study textures classification is Local Binary Patterns (LBP) which have emerged as one of the most popular and extensively studied local texture descriptors. However, a large number of LBP variants has been proposed, to the point that it can become difficult to follow their respective strengths and weaknesses, so it became apparent we're in need for comparative studies regarding the many LBP-related strategies.

In this thesis, we provided a review of the total of 12 LBP variants and some of the classifier methods used along with these LBP variants. We performed evaluation tests for texture classification using these variants on four known databases: (Outex, DTD, Brodatz, Vistex), and as classifier methods, we used two common types of classifiers (SVM, KNN).

The results demonstrated what are strengths and limitations of each LBP variants, and we've seen good performance in the database Outex and Brodatz, but the results weren't as good with DTD and Vistex. We also notice also that the SVM classifier get a better performance than KNN in the case of the Outex and Brodatz Datasets but the KNN classifier performed better in the other two databases.

Despite this comprehensive comparative study, several improvements, additions, and prospects are possible. So as a future work we can:

- Expand the experiments with more databases,
- Study more classifier methods such as Native Bayesian, ANN, CNN…
- Include more LBP variants and other textures descriptors.

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