# BUTTERFLY SPECIES RECOGNITION USING ARTIFICIAL NEURAL NETWORK (ANN)

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# BUTTERFLY SPECIES RECOGNITION USING ARTIFICIAL NEURAL NETWORK (ANN)

**by**

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# LIST OF ABBREVIATIONS

| | |
|---|---|
| ADLBP | Angular Difference Local Binary Pattern |
| ANN | Artificial Neural Network |
| BGC | Binary Gradient Contour |
| BLS | Branch Length Similarity |
| BRINT | Binary Rotation Invariant and Noise Tolerant |
| Ca | Calcium |
| Cd | Cadmium |
| CLBP_M | Completed Local Binary Pattern_Magnitude |
| CLBP_S | Completed Local Binary Pattern_Sign |
| CoLBP | Co-occurrence of Local Binary Pattern |
| CSLBP | Center Symmetric Local Binary Pattern |
| Cu | Copper |
| CULBP | Complementary Uniform Local Binary Pattern |
| disLBP | Discriminative Local Binary Pattern |
| dLBP | Direction coded Local Binary Pattern |
| DLBP | Dominant Local Binary Pattern |
| DNA | Deoxyribonucleic acid |
| DS-LBP | Dual-Scales Local Binary Pattern |

| | |
|---|---|
| EBP | Elliptical Binary Pattern |
| ELBP | Extended Local Binary Pattern |
| FPLBP | Four Patch Local Binary Pattern |
| GLBP | Geometric Local Binary Pattern |
| GLCM | Gray Level Co-occurrence Matrices |
| HGPP | Histogram of Gabor Phase Patterns |
| HOG-TOP | histogram of orientation gradients |
| ILBP | Improved Local Binary Pattern |
| ILTP | Improved Local Ternary Pattern |
| K | Potassium |
| LBP | Local Binary Pattern |
| LBPF | Local Binary Pattern Filtering |
| LBP-TOP | Local Binary Pattern in three orthogonal planes |
| LDP | Local Derivative Patterns |
| LGBPHS | Local Gabor Binary Histogram Sequence |
| LLBP | Local Line Binary Pattern |
| LNIRP | Local Neighbouring Intensity Relationship Pattern |
| LPQ | Local Phase Quantization |
| LQP | Local Quantized Pattern |

| | |
|---|---|
| LTP | Local Ternary Pattern |
| MBLBP | Multiscale Block Local Binary Pattern |
| MBP | Median Local Binary Pattern |
| Mg | Magnesium |
| MLP | Multilayer Perceptron |
| Mn | Manganese |
| MRELBP | Median Robust Extended Local Binary Pattern |
| Na | Sodium |
| Ni | Nickel |
| NILBP | Neighbourhood Intensity Local Binary Pattern |
| NR-LBP | Non-Redundant Local Binary Pattern |
| Pb | Lead |
| POEM | Patterns of Oriented Edge Magnitudes |
| PRICoLBP | Pairwise Rotation Invariant Co-occurrence Local Binary Pattern |
| PTP | Pixel to Patch |
| RBF | Radial Basis Function |
| RDLBP | Radial Difference Local Binary Pattern |
| RLBP | Robust Local Binary Pattern |
| RMS | Root mean square |

| | |
|---|---|
| sLBP | semantic Local Binary Pattern |
| SULBP | Symmetric Uniform Local Binary Pattern |
| tLBP | Transition Local Binary Pattern |
| TMLBP | Threshold Modified Local Binary Pattern |
| TPLBP | Three Patch Local Binary Pattern |
| TS | Texture Spectrum |
| UBN | Unit Branching Network |
| UTGLBP | Uniformly-sampled Thresholds for Generalized Local Binary Pattern |
| WLD | Weber Law Descriptor |
| Zn | Zinc |

# PENGECAMAN SPESIS RAMA-RAMA MENGGUNAI RANGKAIAN NEURAL BUATAN (ANN)

## ABSTRAK

Dalam tahun 2017, terdapat lebih kurang 20,000 spesies rama-rama telah ditemui dalam seluruh dunia. Rama-rama terkenal dengan corak sayapnya yang cantik dan kebaikannya kepada alam sekitar. Dalam pengajian ini, pengecaman spesies rama-rama diautomatikkan dengan menggunakan kecerdasan buatan. Corak yang terdapat di atas sayap rama-rama digunakan sebagai parameter untuk menentukan spesies rama-rama tersebut. Gambar rama-rama ditangkap dan latar belakang gambar tersebut dikeluarkan untuk menyenangkan proses pengecaman. Seterusnya, penghurai corak binari buatan (LBP) digunakan ke atas gambar yang telah diproses. Sebuah histogram yang mengandungi informasi gambar akan terhasil. Rangkaian neural buatan (ANN) pula digunakan untuk mengklasifikasikan gambar tersebut.

# BUTTERFLY SPECIES RECOGNITION USING ARTIFICIAL NEURAL NETWORK (ANN)


## ABSTRACT

In 2017, there are about 20,000 species of butterfly has been discovered all over the world. Butterfly is well known because of its beautiful wings pattern and its benefits to the environment. In this research, butterfly species recognition is automated using artificial intelligence. Pattern on the butterfly wings is used as a parameter to determine the species of the butterfly. The butterfly image is captured and the background of the image is removed to make the recognition process easier. Local binary pattern (LBP) descriptor is then applied to the processed image and a histogram consist of image information is computed. Artificial neural network (ANN) is used to classify the image.

# CHAPTER 1

# INTRODUCTION

## 1.1 Research Background

Species recognition has been one of the research carried out by researchers in near decades, especially when the conservation of endangered species become more common and urgent nowadays. There are a few methods to carry out species identification for all sorts of living organism on earth. Some methods need the individual to be caught then collect sample and statistics to do further investigation. Individual with distinct size, shape and colour can be recognised effortlessly. When it comes to insects, they are small and they may look similar but are from different species. Locust and grasshopper made a good example in this case. Both have very similar appearance such as features and shape. These two species behaved very differently after study has been carried out. Same goes to butterfly, all the butterflies on earth have similar appearance. They are classified under the category of insects. Scientists have classified the butterfly under different categories based on the butterfly wing shape and behaviour. The butterflies have been divided into approximately 135 families.

## 1.2 Problem Statement

It is true that there are a lot of method to do species recognition such as biological identification through DNA barcode and visual recognition. Most of the method will harm or kill the animal. Hence, those methods are not suitable to be applied on the endangered species. A system to recognise the species without capturing and hurting the species is a need.

There are a few problems to be solve in this research in order to meet the research target.

Firstly, the method to use Local Binary Descriptor (LBP) to extract features for further classification needs to be studied. Butterfly can be classify based on observation of pattern on the butterfly wings. Both sides of the wings could have different pattern but it depends on the butterfly species chosen to be studied. Hence, the major problem would be how can the wings pattern observed by human eyes can be digitalize in to information that can be read by machine.

Secondly, method to design and train artificial neural network need to be considered. Factors such as number of inputs, number of output, number of neural network layers and number of neurons in the layers needed to be considered. These factors can affect the classification results and accuracy of the butterfly species identification.

Thirdly, method to evaluate the performance is very important to ensure the butterfly species has been recognised properly. The accuracy of the system is an important factor in determining whether the butterfly species recognition works as expected.

## 1.3 Objectives of Research

The major objective of this research is to automatically identify butterfly species using artificial neural network (ANN). This has been broken down in to smaller objectives to carry out this research more efficiently. The objectives are listed as below.

1. To do butterfly feature extraction using Local Binary Pattern (LBP) descriptor.
2. To classify butterfly species using artificial neural network (ANN) based on information from feature extraction.
3. To evaluate the performance of the butterfly identification through Local Binary Pattern (LBP) descriptor and artificial neural network (ANN).

## 1.4 Scope of Research

This research will focus on the recognition of butterfly species using artificial neural network (ANN). In this research, *ideopsis vulgaris* usually referred as Blue Glassy Tiger butterfly and *hypolimnas bolina* usually referred as Bluemoon butterfly are being chosen. The butterflies that need to be recognise will be captured using any devices. Image processing technique which is Local Binary Pattern (LBP) is used to process the images of butterflies. A multilayer Artificial Neural Network is used to match the processed data to the database and found the correct species.

## 1.5 Thesis Outline

This thesis contains chapters as listed below. These chapters will be explained further on the research from several aspects to achieve the result of research.

Chapter 2 describes the basic concept and principles behind the Local Binary Pattern descriptor (LBP). Besides, this chapter describes the concept and principle of Artificial Neural Network (ANN).

Chapter 3 covers the project methodology and implementation which will further explain the methods and techniques used.

Chapter 4 includes the results of every phase mentioned in Chapter 3. Also, the results are analysed and discussed in this chapter.

Chapter 5 contains the conclusion and research contribution. The recommendation and improvements also being discussed in this chapter.

# CHAPTER 2

# LITERATURE REVIEW

## 2.1 Introduction

This chapter starts with a brief introduction on butterfly species recognition. Next, this chapter proceeds to the introduction of local binary pattern (LBP) descriptor. The working concept and the function of LBP descriptor is described together with some examples on how the LBP descriptor is utilised in the previous work done by other researchers. Other than LBP descriptor, this chapter describes another technique used in image classification, which is the artificial neural network (ANN) technique. In this part, ANN technique is explained on its theory. Some real life application of ANN technique in previous research work are included as well. Lastly, one of the example work done previously on the butterfly species recognition topic, the butterfly species recognition by branch length similarity entropy is included.

## 2.2 Butterfly Species Recognition

Among the five families in the animal kingdom, insects is the most crowded family as it has about one and a half million species. Butterflies, together with moths, both under the *Lepidoptera* order, is the richest team among insects with its more than 170,000 species [1]. Among these 170,000 species, the wing shape, texture and colour vary within a great range. Putting the moths aside, butterflies are classified firstly according to their outer morphological qualities [1]. The figures and patterns found on the butterfly wings play important roles in distinction of species as each species of butterfly has different figures and patterns on their wings.

Previously, identification of butterfly species was done by first glance observation. When the first glance observation did not work, then genital characteristics analysis have to be carried out by preparing genital slides of the collected butterflies through some specific processes using various chemicals. This method was instead time consuming and expensive. Besides, this method was getting less and less popular due to argument and misinterpretation of butterfly species. Misinterpretation happened frequently as the complicated butterfly characteristics are almost similar among the different species.

However, species identification among animals is important to explore evolutionary and development concepts as well as to monitor the spread of pollution and disease vectors and to identify the areas of biodiversity [2]. Butterfly species identification among insects is particularly important as butterflies are associated with crop plants for human and animal consumption. Various identification methods have been introduced in the past. Some of the classical methods are identification by using taxonomic keys, DNA sequencing rely on manual identification as well as classification of butterfly species by highly trained and skilled individuals [2]. In fact most researches on automatic species identification have been devoted to “mass identifications”. Such identification methods classify many images of unidentified specimens amassed in a database through an automated system such as parallel computing, which is equipped with exceptional computing power [3]. These methods are limited in their efficiency and accuracy due to the large computational load and calculation time.

In order to overcome the limitations, new techniques are used in butterfly species recognition. A combination of two stages implementing two different techniques are widely used by researchers due to their obvious advantages compared to the classical methods. The first of the two stages is the use of local binary pattern (LBP) descriptor. The LBP texture analysis descriptor is introduced as a robust descriptor of microstructures in images and it has been used in a large number of computer vision applications such as visual inspection, image retrieval and others. The main advantage of the LBP descriptor are its tolerance to illumination changes and its computational simplicity, which make it possible to analyse images in challenging real time setting [1]. Next, artificial neural network (ANN) technique is used in the second stage in order to execute the classification of texture features obtained from first stage. The ANN technique has been more and more popular in image processing due to its advantage where it only requires the input data and the output data without knowing the processes in between.

In butterfly species recognition, LBP descriptor is firstly used to extract the texture features from the butterfly images. Then ANN technique is used to classify the texture features. Eventually, the butterfly captured in the images can be recognised through the combination of these two techniques. In the following sections, the LBP descriptor and ANN technique will be explained more on their working concept, functionality and their implementation in image processing field other than butterfly species recognition.

## 2.3 Local Binary Pattern (LBP) Descriptor

### 2.3.1 Introduction to Local Binary Pattern (LBP) Descriptor

Local Binary Pattern (LBP) descriptor is defined as a grey scale invariant texture measure, derived from a general definition of texture in a local neighbourhood [1]. It can be seen as a unifying texture model that describes the structure of a texture with micro-textons and their statistical distribution rules. For an image, binary code will be produced for every pixel by thresholding its value with the value of the centre pixel. Initially, the basic version of LBP descriptor only considers the eight neighbours of a pixel. As time passes, the descriptor has developed to include all circular neighbourhoods with any number of pixels.

To understand more about the working concept of a LBP descriptor, it can be decomposed into several steps as shown in figure 2.1. Refer to figure 2.1, the original LBP approach has no pre-processing step. A local neighbourhood structure is a set of pixels take from a square neighbourhood of 3 × 3 pixels. An output of eight bits binary vector is extracted by thresholding the pixels taken from this 3 × 3 square neighbourhood pixels with the value of the centre pixel [4].

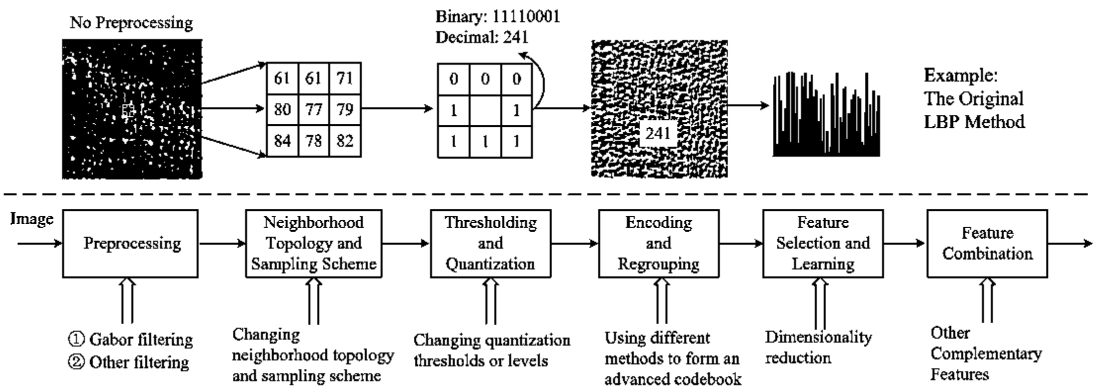


Figure 2.1: The standard process used to extract LBP like features [5].

An original LBP descriptor is favoured as a feature extraction tool due to its simplicity and flexibility. However, it cannot be denied that there are also disadvantages found in LBP descriptor. These limitations include producing long histograms even for small neighbourhoods, capturing only local texture structure and not large-scale structures, limited discriminative capability based purely on local binarised differences, sensitive to image rotation and lastly, limited noise robustness [4].

Aiming to improve the original LBP descriptors, many modifications and extensions have been proposed and thus results in developing a number of LBP variants. However, due to the overwhelming proliferation of these improved methods, taxonomy for LBP variants can be used to describe the improvements made in a step-by-step manner.

### 2.3.2 Taxonomy for LBP Variants

Based on the observation on generally how the LBP variants perform, the taxonomy for LBP variants can be divided into six classes namely traditional LBP, neighbourhood topology and sampling, thresholding and quantisation, encoding and regrouping, combining complementary features and finally methods inspired by LBP [5]. The flow diagram in figure 2.1 shows the steps to be carried out in each class in order to generate a LBP variant. The classes are broken down into individual class below for further explanation in order to understand more on each class and the corresponding steps carried out in respective class.

#### 2.3.2.1 Class 1: Traditional LBP

Back to the year of 1994, the first LBP descriptor is introduced to the world by a group of researchers led by T. Ojala in the research paper "Performance evaluation of texture measures with classification based on Kullback discrimination of distributions" in IEEE International Conference on Pattern Recognition [5]. Yet, only in the year of 2002, LBP descriptor began to attract the interest of the research community. The original LBP descriptors characterised the spatial structure of a local image texture pattern by thresholding a 3 × 3 square neighbourhood with the value of the centre pixel and considering only the sign information to form a LBP [5].

Refer to figure 2.2, an image pixel $x_{0,0}$ is given. By comparing its pixel value $x_c$ with those of its *p* neighbouring pixels that were evenly distributed in angle on a circle of radius *r* centred on $x_{0,0}$, the LBP pattern is calculated as shown in equation 2.1.

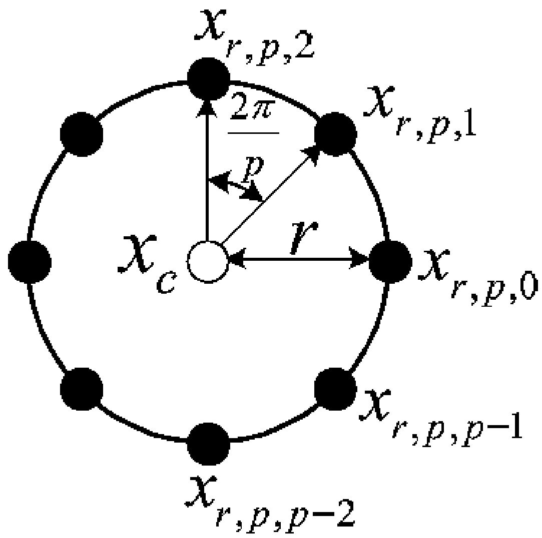


Figure 2.2: A central pixel $x_{0,0}$ and its *p* circularly and evenly spaced neighbours on a circle of radius *r* [4].

$$LBP_{r,p} = \sum_{n=0}^{p} s\left(x_{r,p,n-} x_c\right)2^{n-1} \tag{2.1}$$

where $s(\cdot)$ was the sign function defined as follows:

$$s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

As mentioned in the earlier paragraph, traditional LBP descriptor has its own disadvantages. Three generalisations namely rotation invariant LBP, uniform LBP and rotation invariant uniform LBP are introduced to the traditional LBP descriptor in hope to overcome these known disadvantages. Among these three generalisations, rotation invariant LBP, $LBP_{r,p}^{ri}$ is introduced to overcome the traditional LBP descriptor's sensitivity to image rotation. It is achieved by grouping together those LBPs that are actually rotated versions of the same pattern. Only rotationally-unique patterns are kept. Eventually it leads to significant reduction on feature dimensionality. Uniform LBP, $LBP_{r,p}^{u2}$ is introduced to preserve only the uniform patterns and groups all information contained in the non-uniform patterns. It counts the number of 0/1 or 1/0 transitions between successive bits in the circular representation of the pattern binary code. All patterns with $U > 2$ are called non-uniform patterns and are classified under a single group. Therefore, the $2^p$ original $LBP_{r,p}$ patterns are classified into $p(p-1)+3$ different groups, leading to significant dimensionality reduction. Lastly, rotation invariant uniform LBP, building on rotation invariant LBP and uniform LBP, is introduced to obtain improved rotation invariance and to further reduce the feature dimensionality.

#### 2.3.2.2 Class 2: Neighbourhood Topology and Sampling

Traditional LBP descriptor identifies a neighbourhood as a set of pixels on a circular ring with certain radius from the centre pixel. However, this may not be always effective as different application may require different neighbourhood style. Therefore, a lot of neighbourhood topologies have been defined as shown in figure 2.3. To further explain into these topologies, they are firstly subdivided into three categories, namely anisotropic information, local differences or magnitudes and micro- and macro-structures.

The images from (*b*) to (*e*) in figure 2.3 are the examples of anisotropic information topologies. A basic anisotropic topology is circular-like, such as elliptical neighbourhood in Elliptical Binary Pattern (EBP) and parabolic, hyperbolic and spiral neighbourhood in Local Quantized Pattern (LQP). LQP is expected to provide an increase in discriminative power. Local Line Binary Pattern (LLBP) is way different compared to EBP and LQP, which uses lines in vertical and horizontal directions for LBP computation [5].

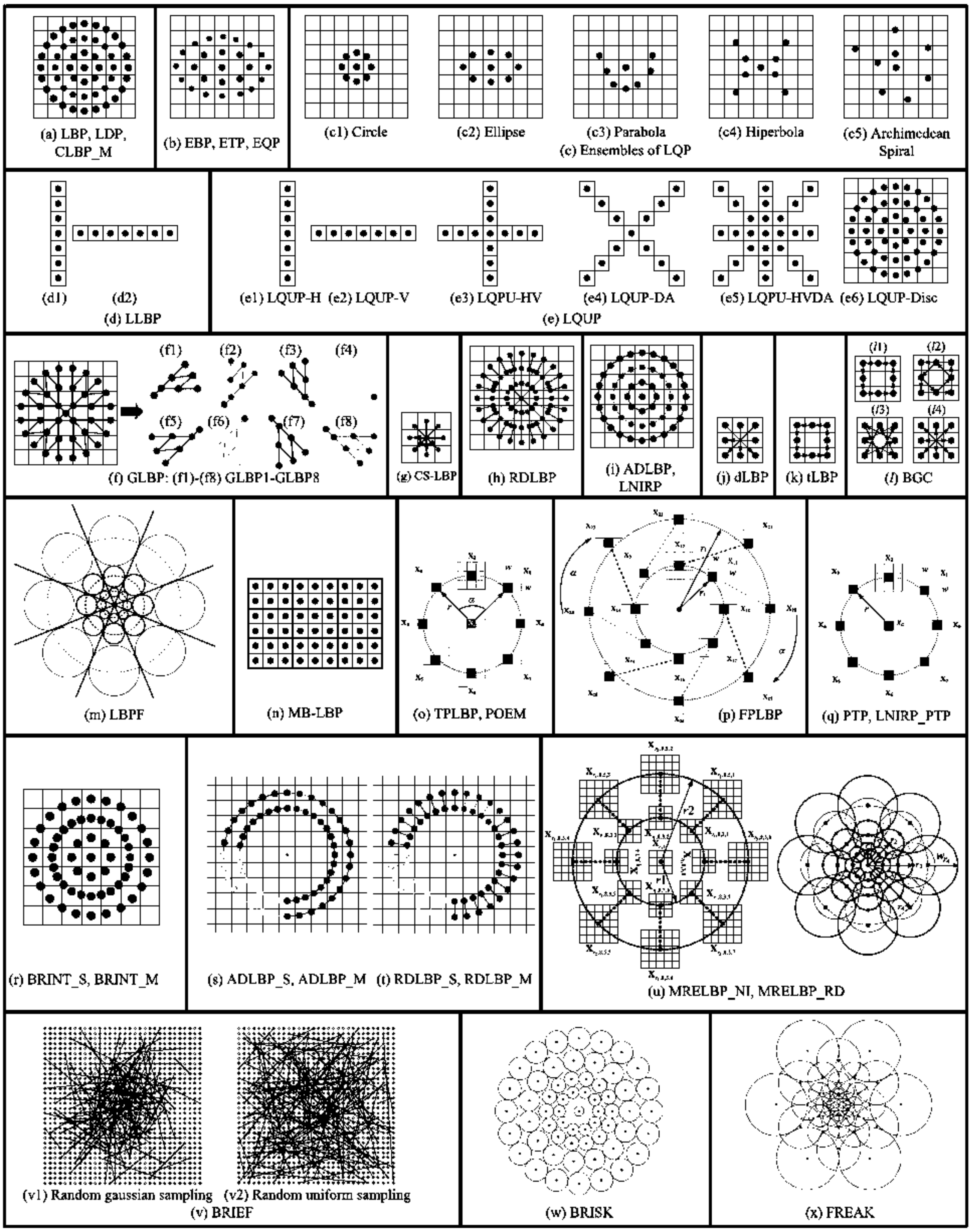


Figure 2.3: Neighbourhood topologies of different LBP variants [5].

Next, local differences or magnitudes topologies are shown in images from (*f*) to (*l*) in figure 2.3. A traditional LBP descriptor threshold the entire neighbouring pixel values against the centre pixel. This thresholding will cause all the relations between pixels in the neighbourhood lose. To remain the relations between pixels in the neighbourhood, local differences or magnitudes topologies among neighbours are used to generate LBP codes. In local differences and magnitudes topologies, the most basic idea was to decompose the local differences into two complementary components: the signs and the magnitudes, which correspond to the Completed Local Binary Pattern_Sign (CLBP_S) operator and Completed Local Binary Pattern_Magnitude (CLBP_M) operator. CLBP_S operator is the same as traditional LBP while CLBP_M operator gives local contrast information [5].

Image (*h*) and image (*i*) in figure 2.3 are showing Radial Difference Local Binary Pattern (RDLBP) and Angular Difference Local Binary Pattern (ADLBP) which measures local differences radially and angularly respectively. Images (*g*), (*l*), (*k*) and (*j*) are showing Center Symmetric Local Binary Pattern (CSLBP), Binary Gradient Contour (BGC), Transition Local Binary Pattern (tLBP) and Direction coded Local Binary Pattern (dLBP). All of them are related to ADLBP in taking angular differences. Local Neighbouring Intensity Relationship Pattern (LNIRP) is similar but it is based on second-order derivatives in the circular direction.

Another two related methods are the Geometric Local Binary Pattern (GLBP) and the Local Derivative Patterns (LDP). GLBP explores changes in intensity on oriented neighbourhoods instead of dense local neighbourhoods while LDP is a general framework to encode directional pattern features based on local derivatives. It means that a (*n*)th-order LDP compares the (*n-1*)th-order directional derivatives at the centre pixel with those at neighbouring pixels.

Images from (*m*) to (*x*) in figure 2.3 show the topologies of LBP variants that are able to capture micro- and macro-structures. Traditional LBP descriptor is known to encode only local micro-texture and being unable to capture nonlocal macrostructure. In this case, patch-based LBP variants are used to solve the problem by integrating over larger areas. Numerous patch-based LBP variants such as Local Binary Pattern Filtering (LBPF), Multiscale Block LBP (MBLBP), Three Patch LBP (TPLBP), Four Patch LBP (FPLBP), Pixel to Patch (PTP), Patterns of Oriented Edge Magnitudes (POEM), Binary Rotation Invariant and Noise Tolerant (BRINT) and Median Robust Extended LBP (MRELBP) are all related but different in the shapes of the patches (either rectangular, square or pixel arc), filtering (raw pixels or filtered values), the nature of the central comparison (single pixel, patch mean or patch median), whether one or multiple rings of patches are used, and whether directional or gradient information is captured [5].

Among these LBP variants, MBLBP is a LBP variant adopting the neighbourhood shown in figure 2.4. A $w \times w$ patch centred on the pixel of interest and $n$ additional patches distributed uniformly in a ring of radius $r$ around it. The LBP computation was done based on comparison of the average values of the neighbouring patches against that of the centre patch. In comparison with traditional LBP descriptor, MBLBP is more robust as it encoded not only microstructures but also macrostructures of image patterns [4].

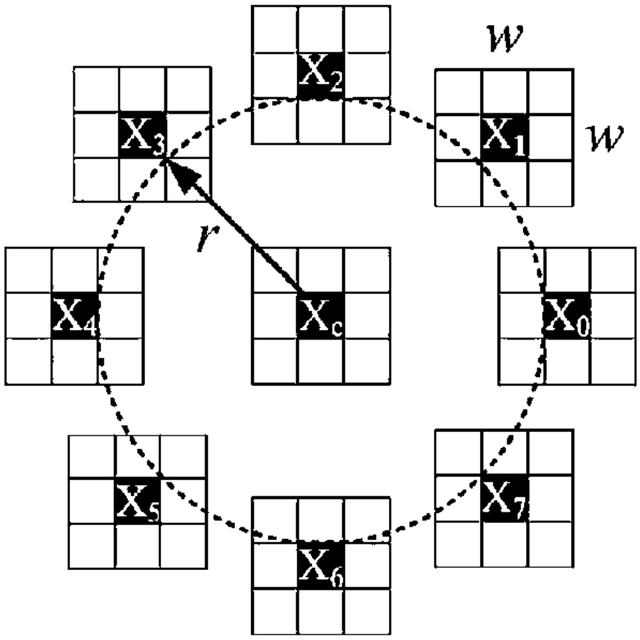


Figure 2.4: A ring of image patches [4].

#### 2.3.2.3 Class 3: Thresholding and Quantisation

Traditional LBP descriptor is highly sensitive to noise since its thresholding operation compares pixels value directly. In order to gain noise robustness and discrimination power, thresholding schemes have been changing as time passes. Overall, these thresholding schemes can be categorised into three categories, the changes in thresholding, the changes in number of quantisation levels and lastly, preserving additional information.

For the category of the changes in thresholding, it actually brings the meaning of changing the pixel value taken as the threshold. For a traditional LBP descriptor, the grey value of the centre pixel is used as the threshold for thresholding. In the case of changing thresholding value, other thresholds are considered. For example, in Neighbourhood Intensity Local Binary Pattern (NILBP) and Improved Local Binary Pattern (ILBP), local mean is taken as the threshold value while Median Local Binary Pattern (MBP) uses local median as the threshold. In certain cases such as Threshold

Modified Local Binary Pattern (TMLBP) and Uniformly-sampled Thresholds for Generalized Local Binary Pattern (UTGLBP), one or more shifted thresholds are used.

In the category of the changes in number of quantisation levels, Local Ternary Pattern (LTP) is introduced. LTP is capable to encode pixel similarity modulo noise using the simple rule that any two pixels within some range of intensity are considered similar [5]. The first approach in this category before LTP was introduced is actually implementing the Texture Spectrum (TS). TS is introduced earlier than LBP. It uses an additional parameter which defines a tolerance for similarity between different grey intensities. LTP is only invented after the researchers are motivated by TS and LBP descriptor.

Lastly, in preserving additional information, the examples are the Robust Local Binary Pattern (RLBP), the Extended Local Binary Pattern (ELBP) and the Improved Local Ternary Pattern (ILTP). RLBP is based on the traditional LBP descriptor. However, it is inspecting consecutive three-bit substrings in non-uniform patterns but at a risk of mapping natural non-uniform patterns to uniform ones [5]. On the other hand, ELBP encodes the sign information and also the magnitudes between the central pixel and its neighbours using some additional binary units while ILTP combines ILBP and LTP in a way that the LTP code is split into positive and negative ILBP codes.

#### 2.3.2.4 Class 4: Encoding and Regrouping

In this class, LBP variants are grouped according to three criteria namely heuristics groupings, co-occurrence groupings and learning strategies. As mentioned before, traditional LBP descriptor produces a long and large histogram even for small neighbourhoods, which then leads to poor discriminative power and requirement on large storage space. At the same time, not all the local patterns are suitable for modelling the characteristics of any textures. Therefore, there is a need to differentiate and group the local patterns according to different criteria.

In heuristics grouping, the aim is to group the local patterns to improve the traditional LBP descriptors. For example, in Symmetric Uniform Local Binary Pattern (SULBP), uniform patterns representing “edge” and “corner” occur more frequently in face images than those representing “line end” and are more discriminative. Complementary Uniform Local Binary Pattern (CULBP) is robust to inverted changes of the background and foreground intensities in detecting objects while semantic Local Binary Pattern (sLBP) groups the uniform patterns with similar arch length and close orientations together [5].

The use of Co-occurrence of LBP (CoLBP) patterns as grouping criteria is referred from Gray Level Co-occurrence Matrices (GLCM). The idea of the back is to consider the joint probability of pairs of LBPs at certain relative displacements. One of the example is Pairwise Rotation Invariant Co-occurrence Local Binary Pattern (PRICoLBP). PRICoLBP can achieve global rotation invariance by sampling the neighbouring point along the unit gradient direction or the unit normal direction at the centre point.

Besides, local patterns are grouped according to their learning discriminative ability. The LBP variants under this group are Dominant Local Binary Pattern (DLBP) and Discriminative Local Binary Pattern (disLBP). DLBP uses the most frequently occurring LBP patterns and discards those seldom occur ones by examining the occurrence frequencies of the rotation invariant LBP groups. Next, disLBP is an improvement of DLBP where it considers the intra-class similarity and inter-class distance during learning.

#### 2.3.2.5 Class 5: Combining with Complementary Features

In this class, strength from different complementary variants is combined to invent more powerful variants. Generally, there are three methods to generate a more powerful variant. The first method is by adding a pre-processing step to the input image prior to LBP type feature extraction. The second method is by combining multiple LBP type descriptors to obtain a powerful one and lastly the third one is by extracting LBP type features and other non-LBP type features at the same time and then fuse two kinds of features together.

In the first method, Gabor filtering is most common used. In comparison, LBP captures small and fine details while Gabor filters encodes appearance information over a broader range of scales. The representative works of this method are Local Gabor Binary Histogram Sequence (LGBPHS) and Histogram of Gabor Phase Patterns (HGPP). In both methods, the image is first convolved with 40 Gabor filters at five different scales and eight orientations. Then, in LGBPHS, the LBP method is then applied to all 40 Gabor magnitude images. In HGPP, the Gabor phase information is encoded for 90 images of the same size as the original image. In the end, the performance is improved for both method when compared to the original LBP descriptor due to richer information from the additional Gabor filtering stage [4].

#### 2.3.2.6 Class 6: Other Methods Inspired by LBP

LBP descriptor has managed to inspire and motivate the development of other related local image descriptors. Local Phase Quantization (LPQ) and Weber Law Descriptor (WLD) are the examples of descriptors inspired by LBP. LPQ is generated by quantizing the Fourier transform phase in local neighbourhoods. It is tolerant to common types of image blurs. On the other hand, WLD works well on texture classification and face detection. It is a 2D histogram of differential excitation reflects the ratio between the relative intensity differences of a centre pixel against its neighbours and the intensity of the centre pixel itself [5].

### 2.3.3 Examples of LBP Descriptor Utilisation

As time passes, more and more LBP variants with different specialities are developed based on the traditional LBP descriptor. These LBP variants are usually designed in order to address the weaknesses of the traditional LBP descriptor such as the limited noise robustness and long histogram produced as an output. Next, two examples of LBP variants utilisation is described in order to understand how LBP variants is being implemented in other research and the purpose of implementing them.

#### 2.3.3.1 Detection of Brain Tumour in 3D MRI Images Using LBP

In a research led by SolmazAbbasi from Shiraz University of Iran, an automatic method for brain tumour detection in 3D images has been proposed. Firstly, the bias field correction and histogram matching are used for pre-processing of the images. Then, the region of interest is identified and separated from the background of the Flair image. LBP in three orthogonal planes (LBP-TOP) and histogram of orientation gradients (HOG-TOP) are used as the learning features. In this research, LBP-TOP is used to extend histogram orientation gradients for 3D images. Figure 2.5 shows the major steps in automatic brain tumour detection in 3D images.

Refer to figure 2.5, LBP-TOP is utilised in the step of feature extraction. In this step, the features are extracted from different textures in such a way that within-class similarity is maximised and the between-class similarity is minimised. The features used in brain tumour segmentation depend on the type and grade of the tumour because different tumours with different grades can be very different in appearance [6].

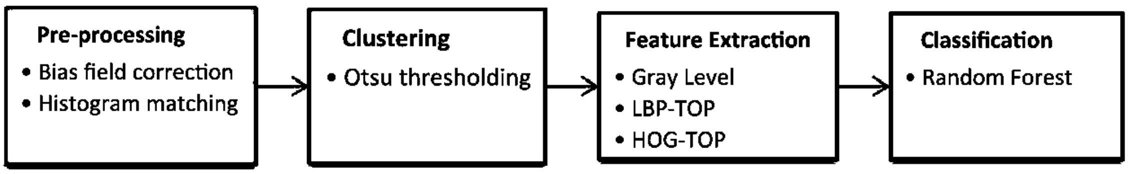


Figure 2.5: Major steps in automatic brain tumour detection in 3D images [6].

The traditional LBP descriptor is only defined with spatial information. It is then extended for dynamic textures analysis. In dynamic texture analysis, each voxel in three orthogonal planes (XY-XT-YT) is considered. Figure 2.6 shows neighbourhood point of each voxel in three orthogonal plane.

X and Y are spatial coordination and T represents times. To be more specific, binary codes are extracted from all voxels in XY, YT and XT planes and specified as XY-LBP, YT-LBP and XT-LBP. Histograms are then computed and concatenated in a histogram. Each voxel is located at the intersection of the three orthogonal planes. In these planes, eight neighbours are delineated for each voxel. The LBP for each voxel is separately extracted based on its location on each plane. The final feature vector is achieved by arranging the values of the LBP [6].

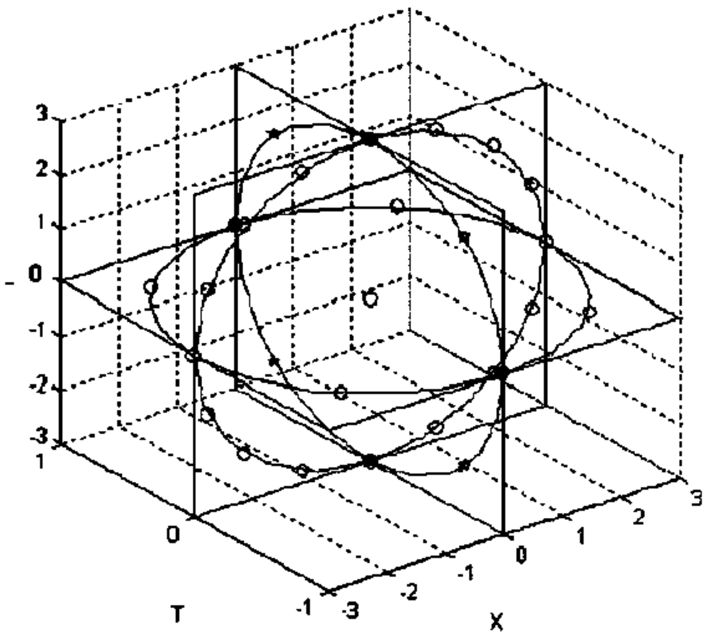


Figure 2.6: Neighbourhood point of each voxel in three orthogonal plane [6].

#### 2.3.3.2 Feature Extraction Algorithm for Plant Leaf Recognition

A group of researchers led by Xuan Wang from Shaanxi Normal University of Xi'an proposed a feature extraction algorithm for plant leaf recognition based on dual-scale decomposition and LBP. Firstly, a plant leaf image is decomposed into several sub-bands with an adaptive lifting wavelet scheme. Secondly, each sub-band is filtered using a group of variable-scale Gaussian filters. Then, LBP descriptor is used to capture both shape and texture characteristics. Non-Redundant LBP (NR-LBP) and Centre-Symmetric LBP (CS-LBP) are used to address the drawback of traditional LBP descriptor where it yields a long histogram despite of the small neighbourhoods. Besides, a new LBP variant, the Dual-Scales LBP (DS-LBP) is introduced in this paper in order to gain a higher robustness on smooth image areas in comparison with the other LBP variants. The histogram of the LBP descriptor at different scales and different sub-bands are determined as features [7]. Finally, a fuzzy *k*-nearest neighbours' classifier is used for matching.

## 2.4 Artificial Neural Network (ANN)

### 2.4.1 Introduction to Artificial Neural Network (ANN)

The Artificial Neural Network (ANN) is a computer system developed to mimic the operations of the human brain by mathematically modelling its neuro-physiological structure [8]. It represents a mathematical model emulating same properties of the human central nervous system as well as rely on adaptive learning and can be used to extract patterns and detects complex trends [9].

Comparing ANN to human brain, neurons as the computational units in ANN is similar to the nerve cells in human brain while the strengths of the interconnections are represented by weights, in which the learned information is stored. ANN consists of layers, namely the input layer, the inter layers (hidden layers) and the output layer. The input layer receives data from the external world, while the output layer presents the processed data to the user. In between of these two layers, the inter layers (hidden layers) are where the data is processed.

In the hidden layers, there are numerous number of neurons responsible for the performance and the length of the ANN. When ANN is applied to an unknown input, the network itself is trained by experience, which means it can generalize from past experiences and produce a new result [1]. Figure 2.7 shows a fundamental representation of an artificial neuron.

Refer to figure 2.7, the inputs to ANN is represented by a symbol $x_n$. Each of these inputs is multiplied by a connection weight that represented by$W_n$. Next, the products of $x_n$ and $W_n$ are summed and then fed through an activation function to generate a result for output [8].

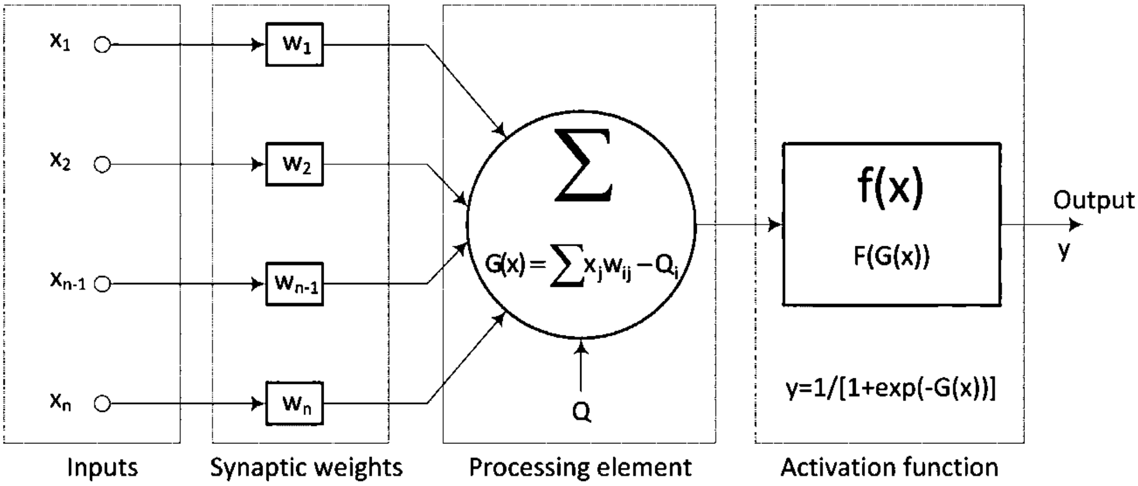

Figure 2.7: Artificial neuron model [1].

The output of the artificial neuron net is determined by equation 2.2 and equation 2.3, the net output is determined by equation 2.4. $Q_i$ is a bias value while $G(x)$ is the activation function.

$$y(t+1) = F[G(x)] \tag{2.2}$$

$$G(x) = \left[\sum_{j=1}^{n} w_{ij} x_j(t) - Q_i\right] \tag{2.3}$$

$$net_i = \sum_{j=1}^{n} w_{ij} x_j - Q_i \tag{2.4}$$

### 2.4.2 Network Training in ANN

Network training is an iterative procedure that begins with initializing the weight matrix randomly [8]. This process involves a forward and a reverse pass. In the forward pass, an input image from the raw data is applied to the input nodes in the input layer. The weighted sum of the inputs to the active node is calculated which is then transformed into output layer using a nonlinear activation function such as sigmoid function through the hidden layers[8]. On the other hand, in the