CHAPTER 4

Osteoarthritis Classification Using Knee X-ray Imagery

4.1 Introduction

The introduction of the texture-based approach for knee-OA classification is discussed in this section. While the graph-based approach using quadtree decomposition and the Convolution Neural Network are presented in Chapter 5 and Chapter 6 respectively. With respect to research methodology presented in Chapter 1 Section 1.3, there were two studies: (i) knee OA detection and (ii) knee-OA stage classification.

For both study (knee-OA and knee-OA stage), the applying of texture based approach for OA classification is considered. The main purpose of knee-OA detection study is to classify OA and normal, while knee-OA stage classification is to classify the stage of OA. In the context of texture analysis, image data SET A (As mentioned in Chapter 3 Sub-section 3.4.1 Region of Interests) was used. A total of 131 images was used for knee-OA detection study the dataset comprise of two groups: (i) 68 images of OA case and (ii) 63 images for normal control (the data set was divided by expert domain from Bangkok Hospital). SET A data set was divided in five groups in the context of OA stage classification : (i) 39 images of *stage 0*, (ii) 19 images of *stage 1*, (iii) 21 images of *stage 2*, (iv) 44 images of *stage 3* and (v) 8 images of *stage 4*.

To be more specific, for both study (OA classification) in this section ten image texture feature descriptors were applied to extract the feature from each ROI. ROIs were identified, include: (i) Later Femur (LF), (ii) Medial Femur (MF), (iii) Lateral Tibia (LT), and (iv) Medial Tibia (MT). The detail of ROIs identification was presented in Chapter 3 Sub-section 3.4.1. An isolate ROI was applied to ten different texture descriptors that are presented in detail in Section 4.2 consider as the next section. As noted in Section 2.5 Feature Selection Methods of Chapter 2.The implementation of texture descriptors to four ROIs or sub-images produced a groups of feature space. In amount of feature spaces contain a lot of features, in these feature are comprise of different feature value and properties, so the selection of feature is very important to produce the good feature vector which this technique was called Feature Selection Technique (As mentioned in Chapter 2). In similar vein, feature selection is a major technique to reduce feature dimensionality in feature spaces. In the knee-OA detection study, five dissimilar feature selection techniques were presented in Chapter 2 were applied. While in knee-OA stage classification applied only one feature selection technique that considered as the best performance of feature selection method from the knee-OA detection study. Make perfectly clear, a schematic of texture base approach is illustrated in Figure 4.1 below:

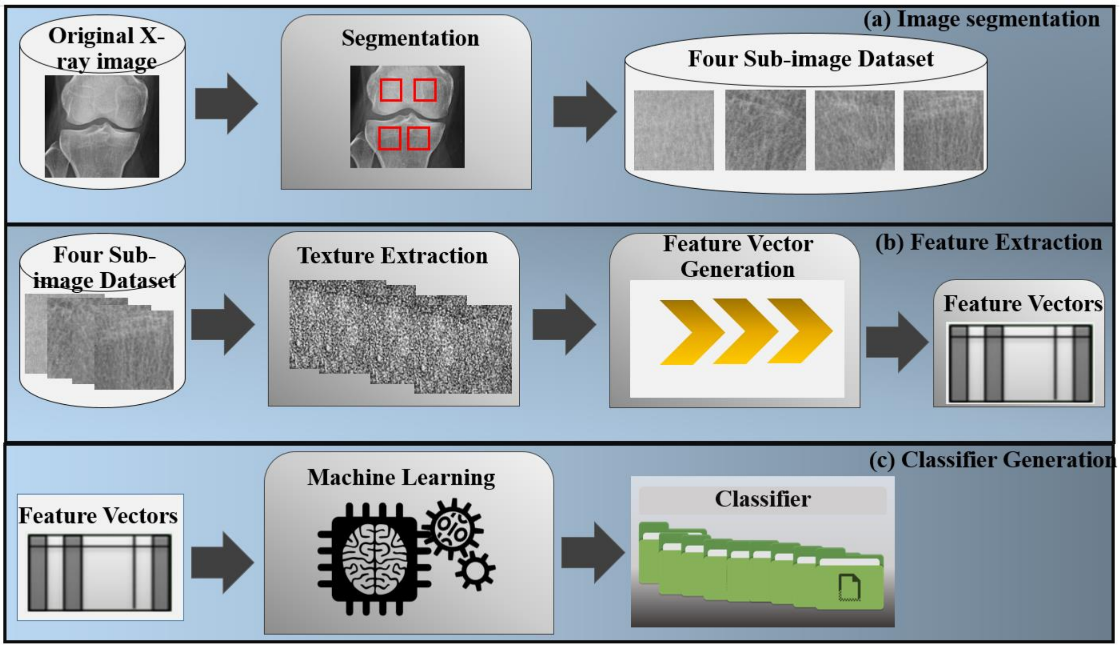

Figure 4.1 The Texture Based of OA classification framework

From Figure 4.1, it can be seen that the texture based approach for OA classification comprises of three main processes: (i) image segmentation, (ii) Feature Extraction, and (iii) Classification Generation. The ROI identification was discussed in Chapter 3 and will thus not discussed further in this chapter. Once the ROIs were obtained, the feature extraction is then command to transform the selected pixel of region into the appropriate from suitable that better for classifier generation. The classifier generation is the process of desire classification model construction using a generated feature (The second process). With respect to the work in this research, nine learning algorithms were applied.

The challenge of this work is how to extract the best saline information of the image based on texture analysis. With the respect to the work here, ten texture descriptors was applied to extract the information of ROIs (Texture descriptor presented in Section 4.2 below). One the ROI was extracted, the feature space was created. In order to make a good feature vector that is suitable to use forward with the learning classifier, the feature space reduction is then applied. In order to reduce the feature space in term of dimensionality and number the feature selection is applied. Thus, the performance of feature extraction process (The second process) that combine of texture descriptor and feature selection techniques to selected the feature vector consist of three sub-processes: (i) Texture Extraction, (ii) Feature Vector Generation, and (iii) Feature Vector Selection. Finally, the feature vector representation was used with learning classifier for the classification process (the third process).

The rest of this chapter is organised as follow: The information of texture descriptors techniques that used in the OA classification works are presented in Section 4.2. Section 4.3 reported the feature selection techniques and classification using in the proposed work. The evaluation of OA classification works are presented in Section 4.4, for knee-OA detection study was evaluated in Sub-section 4.4.1 and knee-OA stage classification was evaluated in Sub-section 4.4.2. The discussion of OA classification works are illustrated in Section 4.5. Finally, the summary of OA classification studies are presented in Section 4.6.

4.2 Texture analysis

In this section, the texture descriptors which were applied in the proposed framework is presented. There are ten texture descriptors were applied include: (i) histogram feature, (ii) Local Binary Pattern, (iii) Completed LBP, (iv) Rotated Local Binary Pattern, (v) Local Binary Pattern Rotation Invariant, (vi) Local Binary Pattern Histogram Fourier, (vii) Local Ternary Pattern, (vii) Local Configuration Pattern, (ix) Haralick feature, and (x) Gabor filter feature descriptor, further information of each texture descriptor is presented as follows:

3.4.1 Histogram feature

The grey image contains of histogram feature which is received by stage of the art of histogram based feature. Three are six features were applied in the study include: (i) Mean, (ii) Variance, (iii) Skewness, (iv) Kurtosis, (v) Energy and (vi) Entropy.

1. Mean is the average of feature I in the grey level of image. Mean can be defined as:

$$\mu = \sum_{j=1}^{n} jP(j) \qquad 4.1$$

where

P(j) is the probability of j, P(j) can be defined as the equation below:

$$P(i) = \frac{H(j)}{M} \qquad 4.2$$

M is the block number and H(j) is the histogram function

2. Variance is a measure of the histogram width that measures the deviation of grey levels from the Mean:

$$\sigma^2 = \sum_{j=1}^{n} (j - \mu)^2 \, P(j) \qquad 4.3$$

where

$\sigma^2$is the variance

μ is the mean

3. Skewness is a measure of the degree of histogram asymmetry around the Mean:

$$skew = \frac{1}{\sigma^3} \sum_{j=1}^{n} (j - \mu)^3 \, P(j) \qquad 4.4$$

where

σ is the standard deviation which is the square root of the variance presented in equation 4.3.

4. Kurtosis is a measure of the histogram sharpness.

$$Kurtosis = \frac{1}{\sigma^4}\sum_{j=1}^{n}(j-\mu)^4\, P(j) \qquad 4.5$$

5. Energy is used to describe a measure of information in image

$$Energy = \sum_{j=1}^{n}[P(j)]^2 \qquad 4.6$$

6. Entropy is a measure of randomness and takes low values for smooth images

$$Entropy = -\sum_{j=1}^{n} P(j)\ \log_2[P(j)] \qquad 4.7$$

4.2.2 Local Binary Pattern

From work [51], LBP was used to label the pixel which was implemented thresholding to the neighbourhood of each pixel come along with the output presented as the binary number. In Figure 4.2 is illustrated the work of LBP operation:

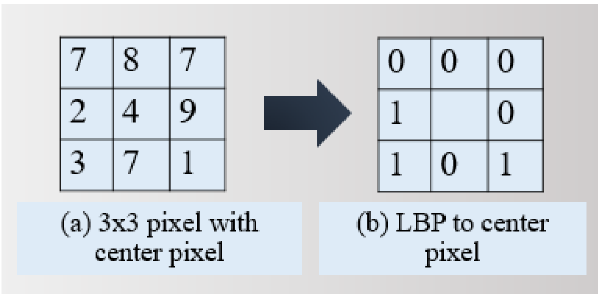

Figure 4.2 LBP Operator

For LBP at pixel (x_c, y_c) can be define as the equation below:

$$LBP_{P,R}(x_c, y_c) = \sum_{P=0}^{p-1} S(i_P - i_c)2^P \quad 4.8$$

where

P presents as the pixel surrounded in the circle neighbourhood.

R presents as the radius of circle.

i_c and i_c present as the grey-level of the centre point.

S(x) presents as the function which S(x) is defined as:

$$S(x) = \begin{cases} 1 & if\ x \geq 0 \\ 0 & if\ x < 0 \end{cases} \quad 4.9$$

In addition, there are some texture descriptors has been proposed as the extension of LBP. In this study, Completed Local Binary (CLBP), Rotated Local Binary Pattern (RLBP) and Local Binary Pattern Histogram Fourier (LBP-HF) are presented below.

4.2.3 Completed Local Binary

In [52], Completed Local Binary Pattern (CLBP) of a local region can be defined by 2 factors: (i) a center pixel and (ii) a local difference sign-magnitude transform (LDSMT). With the reference to the study purpose, LDSMT has been focused. LDSMT consist of two elements: (i) the difference signs (CLBP S), and (ii) the difference magnitudes (CLBP M).

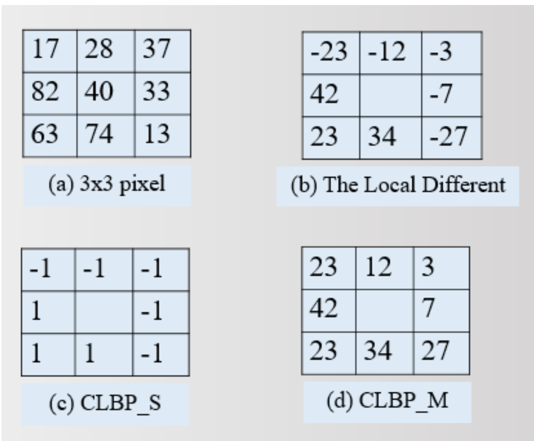

Figure 4.3 The operation of CLBP

4.2.4 Rotated Local Binary Pattern

Rotated Local Binary Pattern (RLBP) [53] or Dominated Rotated Local Binary Pattern (DRLBP) [54] is a technique of LBP rotation around the center pixel of object. In order to get the deep understand of RLBP work, the Figure 4.4 is illustrated the process of RLBP work:

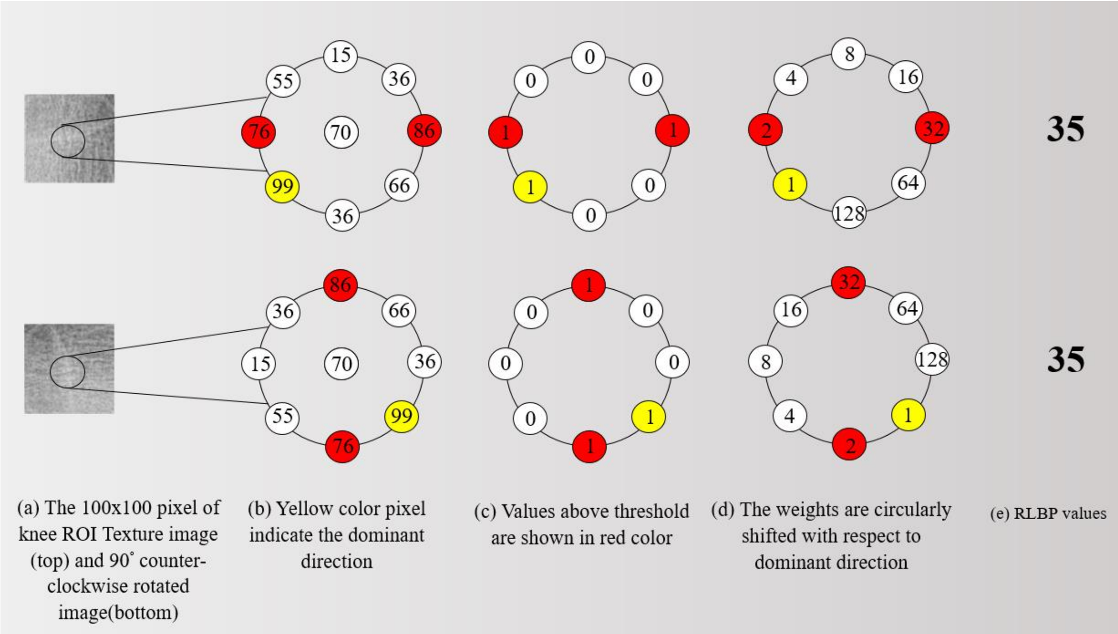

Figure 4.4 The Operation of RLBP

Beside the operation was illustrated in figure 4.4, RLBP can be defined as the equation below:

$$RLBP_{P,R} = \sum_{P=0}^{p-1} S(i_P - i_c)2^{mod(P-D,P)} \qquad 4.10$$

where

D is dominant direction in a neighborhood, D can be formed as the equation:

$$D = \underset{P\epsilon(0,1,\dots,P-1)}{argmax} |i_p - i_c|. \qquad 4.11$$

4.2.5 Local Binary Pattern Rotation Invariant

The Local Binary Pattern Rotation Invariant or LBP_{ri} is presented in this sub-section. LBP_{ri} is another extension technique from LBP with rotation invariant feature. Call back to Equation 4.8 LBP expression, LBP operation can produce of output with 2^P different values, mean that the 2^P different binary can be represented by the P pixels of the neighbour set pixel. With the respect to this study, LBP_{ri} have applied to the pixel with 8 neighbour pixels that represented as the equation below:

$$LBP_{ri}(x, y) = \sum_{P=0}^{7} S(i_P - i_x, y)2^P \quad 4.12$$

4.2.6 Local Binary Pattern Histogram Fourier

In this sub-section, the Local Binary pattern Histogram Fourier (LBP-HF) is discussed. LBP-HF considered as a rotation invariant feature descriptor which is an extention from the LBP uniform. LBP-HF is defined by the first computing of histogram non-invariant of LBPs to the whole object or region, further that the invariant feature of the histogram construct rotationally. The main used of LBP-HF is formed by statistic features which is used to calculate the global features of the LBP histogram by Fast Fourier Transform (FFT). In this case, LBP_{ri} consider as the subset of LBP-HF. The implementation of LBP-HF is represented as the Figure 4.5 below:

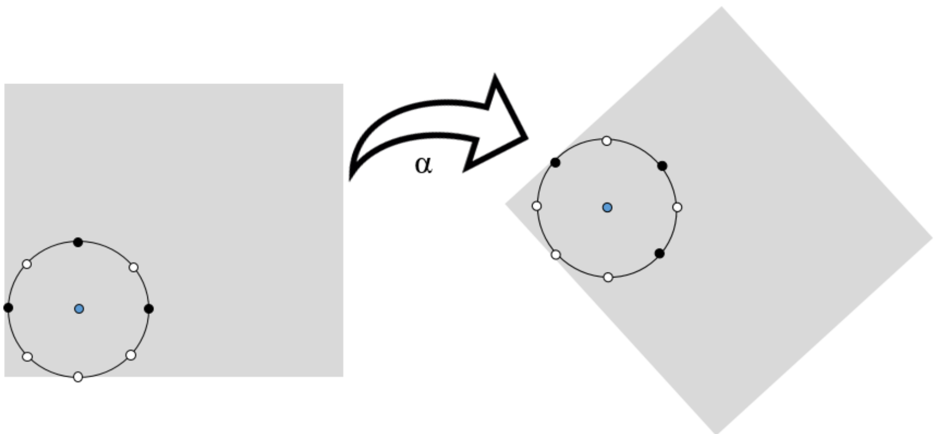

Figure 4.5 The Implementation of LBP-HF

If α = 45°, local binary pattern

10001010 ➔ 00010101

00010101 ➔ 00101010, …,

11111000 ➔ 11110001, …,

At the same time, if α= K * 45°, so, the pattern have to be circularly rotated with K steps.

4.2.7 Local Configuration Pattern

Local Configuration Pattern (LCP) is considered as the rotation invariant image feature description technique. LCP separates image features into two different groups: (i) local structure information and (ii) microscopic configuration or MiC. There are two groups of information architecture include: (i) image configuration and pixel-wise interaction relationship [55]. In local structure information is definitely related to the basic of LBP operation, while in microscopic configuration used for searching the feature of microscopic configuration information. In Figure 4.6 is illustrated the implementation of LCP to local structure and MiC concept

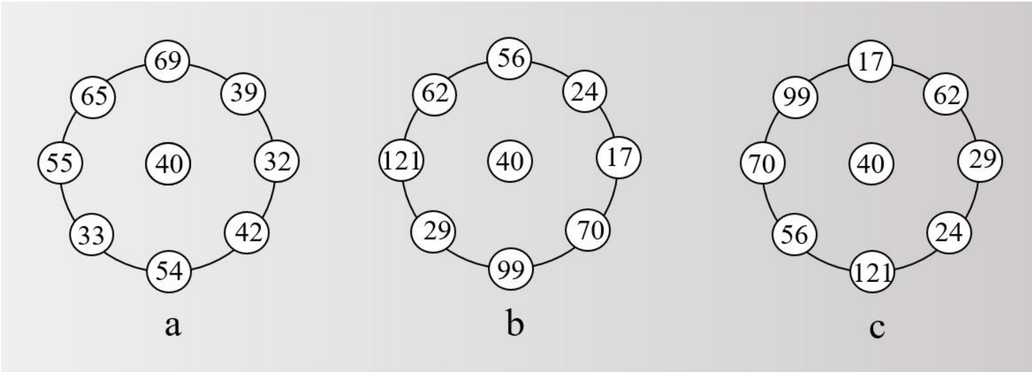

Figure 4.6 The Concept of LCP

Figure 4.6, in figure 4.6(a) and Figure 4.6 (b) are the same in case of pattern type as LBP (all neighbor pixel compare to center pixel value). On the contrary, Figure 4.6 (a) and Figure 4.6(b) are different in case of LBP with local invariant information, while Figure 4.6(b) and Figure4.6(c) are the same because of the same value of invariant. For Figure 4.6(b) and Figure 4.6(c) are different if considered in term of MiC. MiC is based on textural properties which can be formed as the equation below:

$$E(a_0, \ldots, a_{P-1}) = |g_c - \textstyle\sum_{j=1}^{P-1} a_j \, g_j| \qquad 4.13$$

where

g_c is the intensity of center pixel values

g_j is the intensity of neighbored pixel values

$a_j(j0, \ldots, P-1)$ are the weighting parameters relation with g_j

$E(a_j)$ is the reconstruction error regarding model parameters of a_j

4.2.8 Local Ternary Pattern

Local Ternary Pattern (LTP) is described in this sub-section. LTP is one of the development techniques from LBP technique that used to analyse the centre pixel of i_c. As noted in Equation 4.8 LBP, S(x) have only two values, but when applied with LCP the S(x) is instead of 3 values function $S_t(u,i_c,t)$ as the following equation:

$$S_t(u, i_c, t) = \begin{cases} 1 \quad if \quad u \geq i_c + t \\ 0 \quad if \quad |u - i_c| < t \\ 0 \quad if\, u \geq i_c + t \end{cases} \qquad 4.14$$

4.2.9 Haralick feature

In this sub-section presents Haralick feature which is calculated from the Gray-Level Co-occurrence Matrix (GLCM) presents in this subsection. GLCM is considered as one of the most common techniques to represents the image texture. In this case, Haralick which is measured from the statistic of the basic GLCM is divided into 14 feature as the following:

1. Angular Second Moment (ASM) is used to measures the local uniformity of the grey levels

$$ASM = \sum_{i=1}^{n} \sum_{j=1}^{n} P(i,j)^2 \qquad 4.15$$

2. Contrast (standard deviation) is a measure grey level variations between the reference pixel and its neighbour

$$Contrast = \sum_{a=1}^{n} a^2 \; \sum_{i=1}^{n} \sum_{j=1}^{n} P(i,j), |i-j| \qquad 4.16$$

3. Correlation is used to show the linear dependency of gray level values in the co-occurrence matrix:

$$Correlation = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} (ij) P(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y} \qquad 4.17$$

4. Variance is the square root value of a grey level variants between the reference pixel and its neighbour measurement

$$\sigma^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} (i - \mu)^2 \, P(i,j) \qquad 4.18$$

5. Inverse Difference Moment (IDM) is similar in concept to the inverse difference feature, but with lower weights for elements that are further from the diagonal:

$$IDM = \sum_{i=1}^{n} \sum_{j=1}^{n} \frac{1}{1+(i-j)^2} \, P(i,j) \qquad 4.19$$

6. Sum Average is the average of normalized grey tone image in the spatial domain

$$SumAverage = \sum_{i=2}^{2n} i P_{x+y}(i) \qquad 4.20$$

7. Sum Variance is the variance of normalized grey tone image in the spatial domain

$$Sum\ Variance = \sum_{i=2}^{2n} (i - f_8)^2 P_{x+y}(i) \qquad 4.21$$

8. Sum Entropy (f_8) is a measure of randomness within an image

$$f_8 = -\sum_{i=2}^{2n} P_{x+y}(i) \log[P_{x+y}(i)] \qquad 4.22$$

9. Entropy is an indication of the complexity within an image

$$Entropy = -\sum_{i=1}^{n} \sum_{j=1}^{n} P(i,j) \log[P(i,j)] \qquad 4.23$$

10. Different Variance is an image variation in a normalized co -occurrence matrix

$$Difference\ Variance = \sum_{i=1}^{n} i^2 P_{x-y}(i) \quad 4.24$$

11. Different Entropy is an indication of the amount of randomness in an image

$$Difference\ Entropy = -\sum_{i=1}^{n} P_{x-y}(i) \log[P_{x-y}(i)] \quad 4.25$$

12. Information Measure of Correlation 1 (IMC1) is estimated using two different measures

$$IMC1 = \frac{HXY - HXY1}{\max\{HX, HY\}} \quad 4.26$$

where

HXY is the value of Entropy

HX and HY are the entropy of P_x and P_y

$$\text{HXY1} = -\sum_{i=1}^{n} \sum_{j=1}^{n} P(i,j) \log\{P_x(i) P_y(j)\} \quad 4.27$$

13. Information Measure of Correlation 2 (IMC2) is estimated as follows for symmetric

$$ICM2 = \sqrt{1 - \exp\{-2(HXY2 - HXY)\}} \quad 4.28$$

where

$$HXY2 = -\sum_{i=1}^{n} \sum_{j=1}^{n} P_x(i) P_x(j) \log\{P_x(i) P_y(j)\} \quad 4.29$$

14. Maximum Correlation Coefficient (MCC) measure of dependence of random variables in image

$$MCC = \sqrt{\sum_{k=1}^{n} \frac{P(i,k)P(j,k)}{P_x(i)P_y(j)}} \quad 4.30$$

4.2.10 Gabor filter feature

Gabor filter feature descriptor is presented in this sub-section, Gabor is known as one of the texture extraction techniques that used analyse image texture based on specific frequency and specific direction. Gabor filter banks consist of frequencies, orientations and smooth parameters of Gaussian envelope. Gabor filter banks at pixel (x, y) is defined as the equation below:

$$G(x,y) \equiv e^{-\frac{(x-x_0)^2}{2\sigma_x^2}-\frac{(y-y_0)^2}{2\sigma_y^2}} e^{j(\omega_{x_0}x+\omega_{y_0}y)} \qquad 4.31$$

where

ω_{x_0} and ω_{x_0} present as the center frequency of x and y direction

σ_x and σ_y present as the standard of the Gaussian function along x and y direction.

4.3 Feature Selection and Classification

In this section, the feature selection method and learning classifier algorithm which were applied in the proposed framework is presented. As noted in Section 2.5. The five feature selection techniques (CFS, Chi-square, IG, Gain Ratio, and Relief) were applied in this work for OA detection, while CFS is applied for OA stage classification.

For learning classification techniques presented in Sub-section 2.4.3 of Section 2.4. The nine generation classifier presented in Sub-section 2.4.3 were applied in both study of OA detection and OA stage classification.

Finally, the result of each classification go forward to the evaluation process that is discussed in the next section.

4.4 Evaluation

As noted before our research studies was separated into two main objectives: (i) OA detection and (ii) OA stage classification. The detail of evaluation is presented in Sub-section 4.4.1 and 4.4.2 respectively.

4.4.1 Osteoarthritis Detection using texture analysis

In the evaluation of knee-OA detection is presented in this sub-section. The purpose of evaluation was used to produce the evidence that OA condition can be detected efficiency by applying the proposed framework. In this section, the four sets of experiment were evaluated in order to identify the most efficient results for the following objectives:

1. To demonstrate the most appropriate region of interests (ROIs) according to four sub-images presented in Chapter 3 Sub-section 3.4.1
2. To demonstrate the most appropriate texture descriptors in the context of texture descriptors presented in Sub-section 4.2.2
3. To identify the most appropriate feature selection with the respect to feature selection in Section 2.5
4. To identify the most appropriate learning algorithm with the reference to nine learning algorithm discussed in Chapter 2, Sub-section 2.4.3

Ten Cross Validation (TCV) was implemented in this study. To this end, the discussion of each objective, the result were recorded in term of: (i) Area Under Curve (AUC), (ii) Accuracy (AC), (iii) Sensitivity (SN), (iv) Specificity (SP), (v) precision (PR) and (vi) F-measure (FM).

I. Region of Interest results

This sub-sub-section describes on the evaluation conducted to compare the result of applying different four ROIs of SET A (As mentioned in Chapter 3 Sub-section 3.4.1): (i) Medial Femur (MF), (ii) Lateral Femur (LF), (iii) Medial Tibia (MT) and (iv) Lateral Tibia (LT). For the experiment LBP descriptor was used with CFS feature selection (LBP and CFS feature selection were used because the reports in Sub-sub-section 4.4.1-II and Sub-sub-section 4.4.1-III, had revealed that this were appropriate texture descriptor and feature selection, respectively) and a Bayesian Network classifier method as these had been found to work well in the context of OA detection (see Sub-sub-section 4.4.1-IV).The best performance of each ROI is illustrated in Table 4.1 below (best result indicated in bold font with respect to AUC values):

Table 4.1 Region of Interest best results.

ROI	AUC	AC	SN	SP	PR	FM
MF	0.884	0.794	0.794	0.792	0.794	0.794
LF	**0.912**	**0.832**	**0.832**	**0.832**	**0.832**	**0.832**
MT	0.895	0.802	0.895	0.802	0.895	0.802
LT	0.883	0.809	0.809	0.809	0.809	0.809

From Table 4.1 it can be seen that Literal Femur (LF) is the most appropriate one amount of four sub-image of texture analysis for OA detection come with the highest value of AUC of 0.912, while the second highest appropriate went to Medial Femur (MF) with the AUC value of 0.895. It should be suggested that Lateral Femur is first selecting area for texture analysis of OA detection.

II. Texture Descriptor results

This sub-sub-section describes on the evaluation conducted to identify the best algorithm for feature extraction (Texture Descriptor) of the sub-image. Ten algorithm of feature extraction were considered: (i) histogram feature, (ii) Local Binary Pattern, (iii) Completed LBP, (iv) Rotated Local Binary Pattern, (v) Local Binary Pattern Rotation Invariant, (vi) Local Binary Pattern Histogram Fourier, (vii) Local Ternary Pattern, (vii) Local Configuration Pattern, (ix) Haralick feature, and (x) Gabor filter feature descriptor. For the experiment used to compare these 10 algorithms the LF ROI was used as this had been found to produce the best result was presented in the previous sub-sub-section. Again CFS feature selection was adopted together with Bayesian Network classifier for the same reason as before. The best performance of each texture descriptor is illustrated in Table 4.2 below:

Table 4.2 Texture descriptor best results.

Texture Descriptor	**AUC**	**AC**	**SN**	**SP**	**PR**	**FM**
Histogram	0.757	0.695	0.695	0.69	0.695	0.693
LBP	**0.912**	**0.832**	**0.832**	**0.832**	**0.832**	**0.832**
CLBP	0.882	0.763	0.763	0.762	0.763	0.763
RLBP	0.895	0.809	0.809	0.81	0.81	0.809
LBP_{ri}	0.812	0.771	0.771	0.771	0.771	0.771
LBP-HF	0.773	0.71	0.71	0.717	0.71	0.709
LTP	0.816	0.756	0.756	0.761	0.763	0.755
LCP	0.783	0.725	0.725	0.724	0.725	0.725
Haralick	0.695	0.664	0.664	0.67	0.672	0.662
Gabor	0.883	0.786	0.786	0.786	0.786	0.786

With the reference to Table 4.2, it can be seen that Local Binary Pattern or LBP is considered as the best performance in texture descriptor for OA detection work combine with LF ROI can produce the best AUC value of 0.91. For the second best texture descriptor performance went to Rotated Local binary Pattern or RLPB which one of the extenion techniques from LBP, the best result of RLBP produced the second highest of ACU value of 0.895 in case of texture analysis of OA detection amount of four ROIs. Based on Table 4.2, it can be suggested that LBP is the first choice for using in OA detection and the second choice went to RBLP. On the other hands, Haralick feature produced the lowest result of AUC compare to other texture descriptors. It can be suggested that Haralick is the last choice in this case.

III. Feature Selection Techniques results

This sub-sub-section describes on the evaluation conducted to identify the best mechanism for dimension reduction of feature vector of each subimage SET A. Five algorithms of feature selection were included: (i) Correlation-based Feature Selection (CFS), (ii) Chi-Squared, (iii) information gain, (iv) Gain Ration, and (v) Relief feature selection. For the experiments used to compare these five mechanisms the LF ROI and the LBP descriptor were used as this had been found to produce the best result was presented in the previous sub-sub-sections. Again the implementation of Bayesian Network classifier for the same reason as before. The best performance of each feature selection mechanism is illustrated in Table 4.3 below:

Table 4.3 Feature Selection Techniques best results.

Texture Selector	**AUC**	**AC**	**SN**	**SP**	**PR**	**FM**
CFS	**0.912**	**0.832**	**0.832**	**0.832**	**0.832**	**0.832**
Chi-Squared	0.699	0.687	0.687	0.687	0.687	0.687
Gain Ratio	0.709	0.687	0.687	0.687	0.687	0.687
Information Gain	0.699	0.687	0.687	0.687	0.687	0.687
Relief	0.699	0.679	0.679	0.674	0.681	0.677

In Table 4.3 it can be observed that Correlation Based Feature selection (CFS) is the best Texture selectors which applied with LF and LBP to produce the highest value of AUC at 0.912. Gain ration is the second best of texture selector which can produce the value of AUC at 0.709. On the contrary, Chi-squared, Information gain and relief produced the same value of AUC with the value of 0.699. In term of AUC value, it can be suggested that CFS is the first texture selector for knee OA detection applied with LF ROI and LBP texture analysis technique.

IV. Classification Algorithm results

This sub-sub-section reports on the evaluation conducted to identify the best mechanism for generation classifier of learning methods. Nine algorithms of learning methods were considered: (i) Decision Tree, (ii) Binary Split Tree, (iii) Average One-Dependence Estimators, (iv) Bayesian Network, (v) Naïve Bayes, (vi) Support Vector Machine, (vii) Logistic regression, (vii) Sequential Minimal optimization, and (ix) Back Propagation Neural Network. For the experiments used to compare these nine mechanisms the LF ROI and the LBP descriptor were used as this and applied with CFS feature selection had been found to produce the best result was presented in the previous sub-sub-sections. The best performance of each learning algorithm is illustrated in Table 4.4 below:

Table 4.4 Learning Method Algorithm best results.

Learning Method	AUC	AC	SN	SP	PR	FM
C4.5	0.757	0.779	0.779	0.78	0.78	0.779
Binary Split Tree	0.766	0.74	0.74	0.736	0.742	0.739
AODE	0.896	0.809	0.809	0.804	0.809	0.809
Bayesian Network	**0.912**	**0.832**	**0.832**	**0.832**	**0.832**	**0.832**
Naïve Bayes	0.903	0.817	0.817	0.816	0.817	0.817
SVM	0.715	0.718	0.718	0.711	0.72	0.715
Logistic Regression	0.904	0.84	0.84	0.844	0.847	0.839
SMO	0.771	0.771	0.771	0.771	0.771	0.771
Neural Network Back propagation	0.851	0.771	0.771	0.77	0.771	0.771

With the respect to Table 4.4, it shown that Bayesian Network is the best learning method that can produced the highest value of AUC with the value of 0.912, while the second best learning method went to Logistic regression with the AUC value of 0.904. In contrast, support vector machine is the lowest learning method for selection in case of OA detection due to the production of AUC value of 0.715 that considered as the lowest AUC value amount of learning methods applied in the study. In short, it should be suggested that the applying of Bayesian network to LF RI, LBP texture descriptor, and CFS feature selection approach produced the highest AUC value of 0.912.

4.4.2 Osteoarthritis stage Classification using texture analysis

The OA stages classification evaluation is presented in this section, the aim of this evaluation was to present the evidence that conclude that OA stage grading is easily to detect by using the proposed approach. With the respected to Section 4.2, the evaluation of section 4.2 shown that CFS mechanism is the most efficient feature selection techniques. Thus in this evaluation, there are three sets of experiment are discussed as the following three objectives:

1. To identify the most appropriate region of interests (ROIs) to the four sub-images, identified ROIs described in Chapter 3, Sub-section 3.4.1
2. To demonstrate the most appropriate feature texture descriptors according to texture descriptors described in subsection 4.2
3. To demonstrate the most appropriate learning methods with respect to nine learning method mentioned in Chapter 2 Sub-section 2.4.3

In all evaluations, Ten Cross-Validation (TCV) was applied and classification recorded in term of: (i) Area Under Curve (AUC), (ii) Accuracy (AC), (iii) Sensitivity (SN), (iv) Specificity (SP), (v) precision (PR) and (vi) F-measure (FM).

I. Region of Interests best result

This sub-sub-section reports on the evaluation conducted to compare the result of applying different four ROIs of SET A (As mentioned in Chapter 3 Sub-section 3.4.1): (i) Medial Femur (MF), (ii) Lateral Femur (LF), (iii) Medial Tibia (MT) and (iv) Lateral Tibia (LT). For the experiment LBP descriptor was used with CFS feature selection (LBP and CFS feature selection were used because the reports in Sub-sub-section 4.4.2-II and Sub -section 4.4.1 (OA detection study), had revealed that this were appropriate texture descriptor and feature selection, respectively) and a Bayesian Network classifier method as these had been found to work well in the context of OA stage classification (see Sub-sub-section 4.4.2-III).The best performance of each ROI is illustrated in Table 4.5 below (best result indicated in bold font with respect to AUC values):

Table 4.5 Region of Interest best results

ROI	AUC	AC	SN	SP	PR	FM
Medial Femur	0.822	0.569	0.569	0.849	0.580	0.553
Lateral Femur	0.816	0.585	0.585	0.849	0.618	0.577
Medial Tibia	**0.871**	**0.654**	**0.654**	**0.907**	**0.691**	**0.658**
Lateral Tibia	0.828	0.592	0.592	0.833	0.635	0.658

From Table 4.5 it can be seen that Medial Tibia (MT) is the best ROI for OA stages detection with the highest value of AUC of 0.871. On the other hands, LF produce the lowest value of AUC value of 0.816. Finally, it can be suggested that medial tibia region is worked well for OA stages detection in case of texture analysis, while lateral femur is considered as the last choice for ROI selection for OA stages detection.

II. Texture Descriptor best results

This sub-sub-section describes on the evaluation conducted to identify the best algorithm for feature extraction (Texture Descriptor) of the SET A sub-images. Ten algorithm of feature extraction were considered: (i) histogram feature, (ii) Local Binary Pattern, (iii) Completed LBP, (iv) Rotated Local Binary Pattern, (v) Local Binary Pattern Rotation Invariant, (vi) Local Binary Pattern Histogram Fourier, (vii) Local Ternary Pattern, (vii) Local Configuration Pattern, (ix) Haralick feature, and (x) Gabor filter feature descriptor. For the experiment used to compare these 10 algorithms for OA stage classification study, the MT ROI was used as this had been found to produce the best result was presented in the previous sub-sub-section. Again the application of CFS feature selection with Bayesian Network classifier for the same reason as before (the best result of experiment). The best performance of each texture descriptor is illustrated in Table 4.6 below:

Table 4.6 Texture descriptor best results.

Texture Descriptor	AUC	AC	SN	SP	PR	FM
Histogram	0.647	0.496	0.496	0.776	0.418	0.408
LBP	**0.871**	**0.654**	**0.654**	**0.907**	**0.678**	**0.658**
CLBP	0.789	0.569	0.569	0.836	0.58	0.553
RLBP	0.817	0.585	0.585	0.856	0.578	0.559
LBP_{ri}	0.682	0.477	0.477	0.815	0.478	0.451
LBP-HF	0.682	0.438	0.438	0.801	0.418	0.416
LTP	0.741	0.508	0.508	0.824	0.532	0.492
LCP	0.747	0.515	0.515	0.834	0.509	0.503
Haralick	0.644	0.454	0.454	0.801	0.431	0.416
Gabor	0.772	0.523	0.523	0.833	0.537	0.514

With respect to Table 4.6 above, it illustrated that LBP the most efficiency texture descriptor in OA stages detection with the highest AUC value of 0.871. The second most efficiency texture descriptor went to RLBP with AUC value of 0.817. On the contrary, Haralick is the lowest performance of texture descriptor with AUC value of 0.644. As a result, it can be suggested that for OA stages detection of X-ray imagery, LBP is the first choice for selecting texture descriptor, while Haralick is the last choice amount of 10 texture descriptors in the study of OA detection.

III. Learning Method best results

The best learning method result of each technique for OA stages detection is presented. Based on Table 4.5 and 4.6 shown that MT is the best selected ROI and LBP is the best result of texture descriptor for knee screening OA stages detection study, thus the best learning method that consider as the third objective of this evaluation is presented. There are nine popular of learning methods are presented in

Chapter 2 were applied in this evaluation, and the best result of each techniques is illustrated in Table 4.7:

This sub-sub-section describes on the evaluation conducted to identify the best mechanism for generation classifier of learning methods. Nine algorithms of learning methods were considered: (i) Decision Tree, (ii) Binary Split Tree, (iii) Average One-Dependence Estimators, (iv) Bayesian Network, (v) Naïve Bayes, (vi) Support Vector Machine, (vii) Logistic regression, (vii) Sequential Minimal optimization, and (ix) Back Propagation Neural Network. For the experiments used to compare these nine mechanisms the MT ROI and the LBP descriptor were used as this had been found to produce the best result was presented in the previous sub-sub-sections. The best performance of each learning algorithm is illustrated in Table 4.7 below:

Table 4.7 Learning Method Algorithm best results.

Learning Method	**AUC**	**AC**	**SN**	**SP**	**PR**	**FM**
C4.5	0.628	0.446	0.446	0.798	0.41	0.425
Binary Split Tree	0.659	0.438	0.438	0.832	0.46	0.445
AODE	0.848	0.562	0.562	0.82	0.573	0.518
Bayesian Network	0.858	0.615	0.615	0.834	0.635	0.583
Naïve Bayes	0.854	0.623	0.623	0.827	0.691	0.583
SVM	0.612	0.469	0.469	0.772	0.415	0.353
Logistic Regression	**0.871**	**0.654**	**0.654**	**0.907**	**0.671**	**0.658**
SMO	0.762	0.577	0.577	0.846	0.678	0.646
Neural Network Back propagation	0.842	0.654	0.654	0.864	0.678	0.646

In Table 4.7, it can be illustrated that Logistic Regression considered as the best result learning methods with the highest AUC value of 0.871. While Bayesian Network preformed as the best second of learning method with the value of AUC of 0.858. In contrast, SVM produced the lowest AUC value with the value of 0.612. It can be concluded that Logistic regression is the best choice for learning method selection for OA stages detection, while SVM is considered as the last choice.

4.5 Discussion

The discussion of knee-OA detection and knee-OA stage classification are presented in this section. With respect to evaluation of the OA classification studies were presented in the previous section comprises of two studies evaluation: (i) knee-OA detection and (ii) knee-OA stage classification.

For knee-OA detection study, the overall classification result of OA detection presented in Sub-section 4.4.1 illustrated that the proposed texture based approach, using ten different texture descriptors for texture analysis to dissimilar four ROIs, performed well to the knee X-ray image dataset. The main finding from the experiment were divided into four sets:

1. Amount of four sub-image, the performance of LF is better than other sub-images performance that can make the classification is more effective. In term of AUC value measure, the report of evaluation found that LF ROI produce AUC value of 0.912 considered as the highest value.

2. The best result of classification performance in term of texture descriptors mechanism for X-ray image dataset, was obtained by applying local binary pattern (LBP), followed by rotated local binary pattern (RLBP), while haralick is the last texture descriptor amount of ten texture descriptor in the experiment.

3. The most appropriate feature selection mechanism in the experiment of the study was obtain by correlation based feature selection (CFS) with the highest AUC value of 0.912, followed by Gain Ration with the AUC value of 0.709, and then three feature selection mechanism: (i) Chi-square, (ii) Information Gain, and (iii) Relief that all these three method produced the same AUC value of 0.699.

4. The best performance of leaning method identified from the reported evaluation were: (i) Bayesian Network, (ii) Logistic Regression, and (iii) Naïve Bayes, which considered as the top three of learning method with the AUC value of 0.912, 0.904, and 0.903 respectively, thus Bayesian network produced a slightly better overall performance than Logistic Regression, while Naïve Bayes almost equal to Logistic regression classifier.

For knee-OA detection study, the overall classification result of OA stages classification presented in Sub-section 4.4.2 identified that the proposed texture based approach, using ten different texture descriptors for texture analysis to different four ROIs, performed well to the knee X-ray image dataset. The main finding from the three sets of experiment conducted were:

1. The best classification performance in term of region of interest or ROI, for knee X-ray image dataset, was obtained by the implementation of Medial Tibia ROI, followed by Lateral Tibia and Medial Tibia with the value of AUC of 0.871, 0.828, and 0.822 respectively.

2. The most appropriate texture descriptors mechanism in the experiment of X-ray image dataset study, was obtained by applying local binary pattern (LBP) with the AUC value of 0.871, followed by rotated local binary pattern (RLBP) with AUC value of 0.817, then completed local binary pattern with the AUC vale of 0.789, while haralick is the last texture descriptor amount of ten texture descriptor in the experiment with the lowest value of AUC of 0.644.

3. The best classification performance in term of leaning method identified from the reported evaluation were: (i) Logistic Regression, (ii) Bayesian Network, and (iii) Naïve Bayes, which considered as the best three learning method with the AUC value of 0.871, 0.858, and 0.854 respectively, thus Logistic Regression produced a slightly better overall performance than Bayesian Network, while Naïve Bayes almost equal to Bayesian Network classifier.

In conclusion, the OA classification studies of the texture based approach in this chapter. With the respect to the discussion of knee-OA detection and knee-OA stage classification study, the main findings of OA classification were comprised into four sets of experiment:

1. In OA detection study the most appropriated ROI referred to the LF ROI, while in OA stages detection the most appropriated ROI went to MT ROI. Thus, it can be suggested that for OA detection the Femur region is more important than Tibia region. On the other hand, for OA stages detection the Tibia region should be selected at the first choice, due to the performance is better than Femur region.

2. The best performance of Texture descriptor of both OA detection and OA stages detection went to LBP texture descriptor and followed by Rotated LBP or RLBP.

3. The most appropriated feature selection technique amount of five methods in OA detection was performance by CFS feature selection techniques, while in OA stages detection had applied only CFS.

4. The best classification result of OA detection was performance by classifier generation obtained by Bayesian Network, follow by Logistic Regression, and then Naïve Bayes classifier. In contrast, in OA stages detection was obtained by Logistic Regression, Bayesian Network, and Naïve Bayes method. In conclusion, for both study of OA detection and OA stages detection best classification result in term of classifier generation followed by the best three classifier: (i) Bayesian Network, (ii) Logistic Regression, and (iii) Naïve Bayes.

4.5 Summary

To summary, the chapter presented the texture based approach on knee OA detection and knee OA stages detection study. For OA detection study base on texture was presented in Section 4.2 and OA stages detection was presented in Section

4.3. Base on the reported of each section shown that: (i) Lateral Femur is the best suitable ROI for OA detection, while Medial Tibia is the most efficient ROI for OA stages detection, (ii) LBP is the best texture descriptor for both study, (iii) CFS is play the most significant feature selection in OA detection, while OA stage use only CFS, and (iii) Bayesian Network, Logistic Regression, and Naïve Bayes is the most three efficient learning method for both study.