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Hybrid Statistical Feature Extraction Method LPB – EDMS for Shape Recognition Dataset

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***Abstract*—Invariant descriptor for shape and texture image recognition usage is an essential branch of pattern recognition. It is made up of techniques that aim at extracting information from shape images via human knowledge and works. The descriptors need to have strong Local Binary Pattern (LBP) in order to encode the information distinguishing them. Local Binary Pattern (LBP) ensures encoding global and local information and scaling invariance by introducing a look-up table to reflect the uniformity structure of an object. It is needed as the edge direction matrices (EDMS) only apply global invariant descriptor which employs first and secondary order relationships. The main objective of this paper is the need of improved recognition capabilities which achieved by the combining LBP and EDMS. Working together, these two descriptors will add advantages to the program and enable the researcher to investigate the weaknesses of each one. Two classifiers are used: multi-layer neural network and random forest. The techniques used in this paper are compared with Gray-Level Co-occurrence matrices (GLCM-EDMS) and Scale Invariant Feature Transform (SIFT) by using two benchmark dataset: MPEG-7 CE-Shape-1 for shape and Arabic calligraphy for texture. The experiments have shown the superiority of the introduced descriptor over the GLCM-EDMS and the SIFT.**

Keywords- Feature Extraction, Local Binary Patterns(LBP), Edge Direction Matrixes(EDMS), Classification.

I. INTRODUCTION

Pattern recognition is a simulation of different mathematical, statistical and heuristic techniques used for achieving a better human performance [1]. Similarly, it helps in making machine learning process and pattern detection more concrete and reliable in computer implementation. It has become significant in many applications such as biology, psychology, medicine, marketing, computer vision, artificial intelligence and remote sensing which requires the structural observations [2]. Feature extraction is considered one of the very vital segments in pattern recognition applications [3]. He also claimed that the effectiveness of each feature extraction technique is highly associated with the distinguishing similarities of patterns that belong to each identical class from other patterns or noise. Therefore, the two standard approaches to the feature extraction phase are the local and the global. The local feature extraction approach involves disconnected parts of an image, such as lines, edges, corners, shapes and sub-image regions. This technique explains the image features that have been manipulated after the segmentation process during the pre-processing stage. Thus, the output of local features depends on the accuracy of the segmentation stage. Assure that the local technique could not be applied for different classes. The global feature technique has to do with the overall or sub-regional analysis of the natural image. Usually, it is carried out with the use of texture analysis methods which extract the global properties of the texture of the input image used as general characteristics in the process of recognition. Hence, these two techniques can perform with high precision in classification of more complex datasets. The main objective of this paper is to improve and enhance the invariant statistical feature extraction method based on shape and texture recognition. The shape analysis and texture feature analysis method and their challenges are discussed. Anumber of texture analysis and shape recognition techniques have been proposed over the last twenty years for the textural images feature representation. Hence, this chapter reviews previous work on feature extraction.

II. RELATED WORKS

Feature extraction techniques are made of two categories namely global and local analysis.

A. *Global Feature Extraction Approach.*

Different methods of feature extraction have been proposed based on various approaches. One of the methods was proposed [4]. This method was developed by hybridizing statistical analyses of edge pixels with geometrical relationship and was applied on Arabic calligraphy images to recognize the optical font. The global features extraction approach is one of the classifications techniques of feature extraction [5]. The Gray Level Co-occurrence Matrix (GLCM) [6] and the Gray-Level Difference Method (GLCM) [7] represents the second-order statistics though the two similar methods. The GLCM is widely adopted statistical method in the texture feature extraction [8]. GLCM is suggested [6]. GLCM matrix produces values and describes the distribution occurrences in the image. Gray-level transformations calculated based on displacement and angular rotation parameters, giving four gray-level co-occurrence matrices at 0, 45, 90,135 degrees orientation as shown in Figure 1 cells 1&5 are , cells 2 & 6 are , cells 3&7 are , and cells 4 & 8 are nearest neighbors. For an image having a spatial resolution Nx * Ny and gray scale level 256, the angular relationship between pairs at distance d=1 between pixels is as follows: At orientations (horizontal) the co-occurrence matrix contains 2Ny (Nx-1) nearest horizontal neighbour pairs.

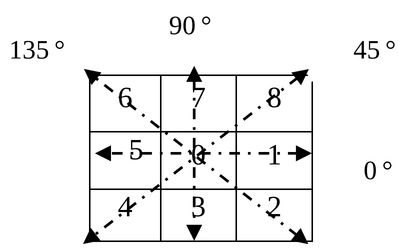


Figure 1. Neighbors Relationship.

[9] Presented, Geometrical with Structural Features and edge direction matrix (EDMS) hybrid features extraction methods for online Arabic character. Another features extraction technique of GLCM (Gray Level Co-occurrence Matrix) and EDMS (Edge Direction Matrixes) for character recognition method was proposed by [10].

The Gray GLCM shows the matrix distribution occurrences in selected images. This is shown in the below formula where 'c' is identified as a GLCM and I is a n × m image and (x, y) is a pixel pair that indicate the gray level value of i and j. The outcome of the result is a formation of matrix that demonstrates the gray scale occurrence of any pair of two pixels. The number of feature is 36 that have been derived from the matrix.

B. *Local Feature Extraction Method.*

LBP was first introduced by [11] for texture classification and it has proved to be a power full feature for texture classification. Combination of LBP and the Histogram of oriented gradients (HOG) classifier improves the detection performance significantly on some data sets. The novel descriptor is capable of improving the capabilities of a typical pattern classification system to recognize the image and it draws descriptors provided by integrating two region descriptors efficiency in recent decades. However, the feature extraction method needs to be improved in order to increase the capabilities of recognition by using formulae. This is aimed at exploring other through the completion of each other and identifies their weaknesses.

The most useful properties of the moments and constants related to the moment of its durability and the presence of noise is combined with global information and encoding mechanism behaviour under conditions of constant measurement, translation and rotation, along with the local nature of the LBP [12]. Another local feature extraction technique is Geometrical Feature (GF) topological analysis method introduced by [13]. GF combined some feature extraction techniques such as zoning, thinning, geometrical features and contours [14] [15]. In this method image is segmented into 5 vertical and 5 horizontal zones and then normalized into 20 × 20 pixel size afterwards, each character image and vertical zones divided into a 20 × 4 matrix and horizontal zones into a 4 × 20 matrix, can be seen in Figure 2.

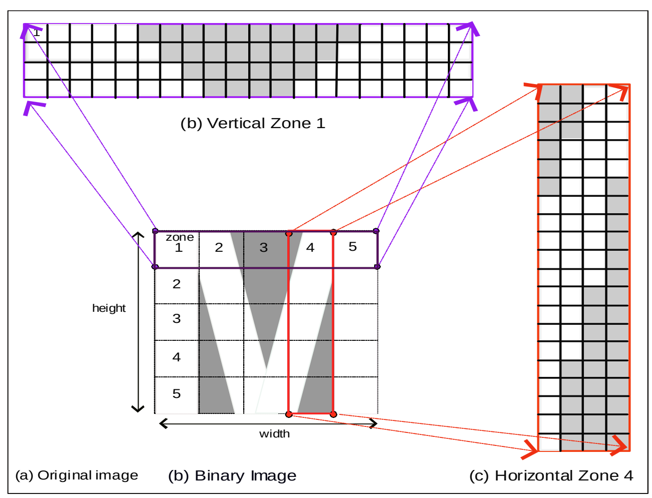


Figure 2. Sample of binary character images in GF source: (Abdullah et al. 2010)

The Scale Invariant Feature Transform (SIFT) algorithm is a special description proposed by [16]. SIFT method used to find, locate and describing features in an image and allows them to be matched robustly between images. This can be achieved by invariant to scale, rotation, affine transform and invariant to illumination changes. Besides that this descriptor has highly distinctive power to identify the images unique feature from the large collection of database. The SIFT descriptor share some proprieties that are similar to the neurons inferior temporal cortex properties which is used to recognizing objects in primate vision [17].

C. Combination of Global and Local Feature Extraction Techniques.

The global features is called for the features which is consequent from the shape of a word contour while the local features results from the geometric characteristics of the word. Combining global and local features for the purpose of handwritten recognition is proposed by [20] which is based on offline handwritten- recognition.The recognition system takes as its input the isolated handwritten word image. In this research two set of features were extracted which are local features and global features. Local features are taken from the word sub-character units and global features consider the word as a whole.

For the purpose of local feature extraction, a- segmentation task needs to be performed in order to segment images to the smaller object than the original character images. Fast left to-right method proposed [21] is applied to the character images to segment the original images.

For recognition stage, the PRG vector is applied as the input to the multi-layer perceptron (MLP) as the classifier. Finally, the results of two classifiers HMM and- MLP are combined by using the frame work to recognize the handwritten word images. The output of the HMM classifier which is a ranked list on the N-best results with estimation of a posteriori probabilities is- combined with output of neural network which is N-best results in order to generate a- composite score which is a weighted combination of both classifiers output .

$$R_{score} = \alpha \log(HMM_{score}) + \beta \log(MLP_{score}), where \alpha + \beta = 1$$

By applying this equation, the new R_{score} which is the composite score of the word is- produced. α and β are the weights which are related to HMM and MLP recognizers.

III. PATTERN RECOGNITION

Humans have different ways of understanding the issues and solving the problems.Many factors that influence humans to understand issues of pattern recognition include but not limited to age , knowledge, experience, senses, mental abilities and disabilities. Tremendous research efforts have been recorded in many other areas of Computer science and Artificial Intelligence (AI) part of which it is being exploited for pattern recognition. Artificial Intelligence (AI) is a system developed using computer simulation to create machines or robots (human machine) that can act just like human beings. It is expected that such machine should be able to think, speak, learn, move, touch and feel the same way human beings act [19]. AI as described by is a technology considered and rated worldwide as critical and of high technical standard. Additionally, rated also as an AI is the space and energy technologies and the three considered the highly rated three technological breakthroughs of the world since 1970s. AI has many areas of research that includes gaming, robotics, language processing, intelligence, machine learning, data mining, genetic programming and neural networks.Each of these areas has some of the characteristic of living creatures[22].

Pattern recognition plays significant role in AI and It is an object that has a specific name or identification which possess some unique features that looks different from others. In AI Pattern Recognition (PR) is designed to create machines that would be able to observe, recognise, categorise, differentiate and perceive their features pattern [23] It is a very important technique that provides many useful applications in our lives. Pattern Recognition (PR) as stated by [24]is used in so many applications ranging from data mining, industrial automation, biometric recognition, multimedia database retrieval, imaging, military, medical, language processing, speech recognition, remote sensing to many more.

A. Shape Recognition.

Shape features play an important role to describe the object and image. Shape consists of colour and texture which is important to identify the object and image as well. However, for some critical reason it becomes difficult to describe the shape, for example, three dimensional objects (3D). When 3D objects areprojected onto a 2D (two dimensional) plane (like photograph image), it looses some the objects information.

Contrary to texture and colour, the features of shapes could be extracted when performing image segmentation like separating the foreground from the background as distortion, occultation and noise do corrupt images. Shape recognition is one of the popular research areas for the last thirty years [25] Many researchers proposed different types of shape representation techniques for retrieving uniform shapes from a reference database. There are two categories in shape representation technique. These are i) Contour-based descriptors and ii) Region-based descriptors. Contour-based technique is a method of extracting boundary image of shapes for better understanding of the shape while extracting information about contour shape uses discrete or continuous method approach can be used for.

various shapes characteristic. Continuous approach derived the feature vector from the entire shape boundary;

discrete approach breaks the shape boundary into segments called primitives and use polygonal approximation and curvature decomposition techniques.

B. Texture Analaysis.

Humans are able to recognize and distinguish between textures very easily, but when humans tried to discuss the textures, find it difficult. Usually, humans are focusing on textures visual or tactile characteristics and define a texture as texture as striped, smooth, homogeneous, irregular and rough. Texture is considered by humans as another form of a visible element. Structure of the texture could be associated with repetitive patterns. The repetition could be in accordance with rule of placement . It is important to note that methods of analyzing texture to describe image extraction receive a global acceptability. image contains fixed textures if local statistical set of image or other local properties are fixed, moderately changeable, or relatively periodical. Textures are used for early visual information processing, exceptionally for classifications.

Many studies make use of information on image texture to identify the features of images in order to distinguish between images. As such, texture analysis techniques are beneficial in several spheres of pattern recognition, such as weather image recognition [26] medical image recognition, document image analysis and recognition [27], satellite image recognition [28], fingerprint [29], iris recognition [30] and biometric recognition such as face [31].

IV. FEATURE EXTRACTIO .

Feature extraction is a basic process in pattern recognition. It can be defined as a special form of dimensionality reduction. Feature extraction involves simplifying the large set of data accurately. Feature extraction can be define as , extraction of raw data from most relevant information for classification purposes while attempting to improve on the between-class pattern variability . According to the definition of feature extraction, it is a complex topic and often considered as an art rather than being science because of the difficulty to measures. Feature extraction method is one of the complex areas in pattern recognition as an example shape recognition .

Feature extraction methods are complex process and their applications differ from one to another. It is not necessary that one applications method will successfully work in another application. However it is an essential, when discussing shape recognition system. Some of the feature extraction methods adopt grey level sub-images of single characters while others use multiple (4 or 8) connections of segmented symbols from symbol contours, thinned symbols, skeletons and from the binary raster image. Additionally, the extracted features must be identical to chosen classifier. For structural or syntactic classifiers, gamma-based characters or graph descriptions were found to be suitable.

V. METHODOLOGY

In this paper, different experiments have been implemented. This includes the methodology applied during the feature Extraction using two method doing hybrid between then (LBP) and (EDMS) and classification recognition stage using theMulti-layer neural network with back propagation (MLBP) and random forest (RF). and different datasets have been used for each form of the experiments The MPEG-7 Core Experiment CE- Shape-1 is one of the most well-known benchmark datasets .

Is one of the most well-known benchmark datasets used in pattern recognition [18]. The selected classes were the cup, beetle, elephant, bone, carriage, camel, fly, chopper, bat, brick, device7, bottle, device0, face, bell, children, flatfish, teddy, fountain, rat, heart, horseshoe, glass key, step, apple, ray, watch and shoe. Figure 3 show examples.

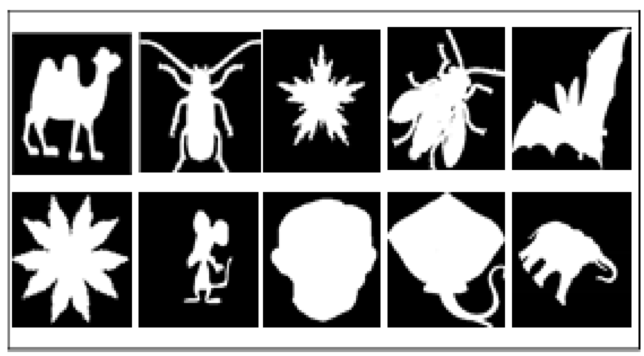
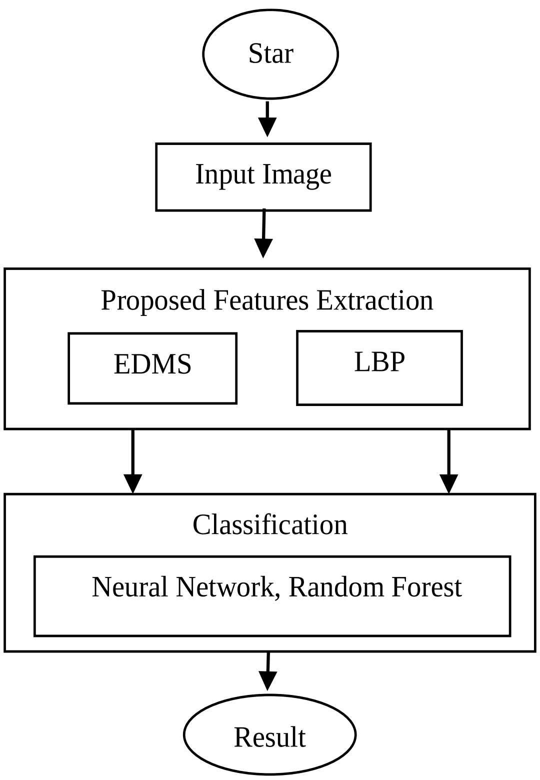


Figure 3. Examples of some different shapes of the MPEG-7 CE-Shape-1.

The Arabic calligraphy dataset is made up of several types of images of Arabic calligraphy scripts there are altogether 700 samples, with 100 samples from each type of image: Thuluth, Kufi, Persian, Diwani, Andalusim, Roqaa and Naskh. The dataset samples were gathered from several sources, such as books, documents, artistic works, calligraphy software products and the internet. Samples of each calligraphy type in this dataset can be seen in Figure 4.

Figure 4. Examples of the Arabic calligraphy datasets.

The proposed method:



A. EDMS Features

In this research, the first method is discussed together with its advantages:

Eight adjoining kernel matrices were applied and each pixel was linked to two neighbouring pixels. A connection was established between the scoped pixel, S(x, y), and its neighbouring pixels, as illustrated in Figure 5(a). The eight pixels were used to change the surrounding values into the position values as shown in Figure 5 (b). Based on the previous illustration, this method was presented according to two perspectives: Finding the first order relationship, and finding the second order relationship.

(x-1,y-1)	(x,y-1)	(x+1,y-1)
(x-1,y)	S(x,y)	(x+1,y)
(x-1,y+1)	(x,y+1)	(x+1,y+1)

(a)

135 °	90 °	45 °
180 °	Scoped pixel	0 °
275 °	270 °	315 °

(b)

Figure 5. Eight neighborhoods and their angle with second pixel.

In the first EDMI matrix, each cell carries a position of between 0 to 315 degrees based on the pixel neighbourhood association. The relationship between the pixel values can be ascertained by calculating the occurrence of the EDM1 values, while taking into consideration the edge image of each pixel in relation to two pixels. The relationship of the scoped pixel in the edge image is represented by Edge(x, y). The following algorithm was used for calculating the EDM1:

Algorithm for calculating the EDM_1

For each pixel in edge
EDM1 (2, 2) = EDM1 (2, 2) + 1.// Scoped
If pixel (x, y + 1) = black, then // 0 °
EDM1 (2, 3) = EDM1 (2, 3) + 1.
If pixel (x + 1, y – 1) = black, then // 45°
EDM1 (3, 1) = EDM1 (3, 1) + 1.
If pixel (x, y – 1) = black, then // 90°
EDM1 (2, 1) = EDM1 (2, 1) + 1.
If pixel (x –1, y – 1) = black, then // 135°
EDM1 (1, 1) = EDM1 (1, 1) + 1.
If pixel (x, y – 1) = black, then // 180 °
EDM1 (1, 2) = EDM1 (2, 3) + 1.
If pixel (x – 1, y + 1) = black, then // 225°
EDM1 (1, 3) = EDM1 (3, 1) + 1.
If pixel (x, y + 1) = black, then // 270 °
EDM1 (2, 3) = EDM1 (2, 1) + 1.
If pixel (x +1, y + 1) = black, then // 315 °
EDM1 (3, 3) = EDM1 (1, 1) + 1.
End

IN Figure 6, the scoped pixel (*) represents 180 ° for X1 and 45 ° for X2. That means the pixel presents two relationships in (EDM1).

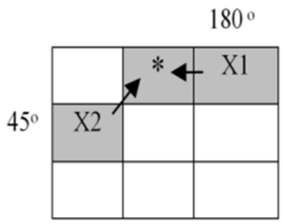
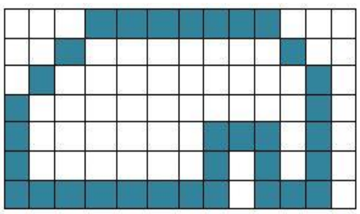


Figure 6. Example of two neighboring relationships of the scoped pixel.



	135°	90°	45°	
	5	11	5	
180°	17	33	17	0°
	5	11	5	
	225°	270°	315°	

(a) (b)

Figure 7. (a) The edge image and (b) is it's EDM1

The second order matrix, EDM_2, which is 3 × 3, is regarded as an edge direction matrix and carries the relationship representation for each pixel. The most significant pixel relationship was detected by measuring the occurrence of each value in the EDM2. In instances where more than one angle had the same occurrence number, the smaller angle would be selected first, followed by the other small pixels subsequently. The algorithm for the second order relationship is given as follows:

Algorithm for calculating the EDM2
Step 1: Sort discerningly the relationships in EDM1(x, y).
Step 2: For each pixel in Edge(x, y),
Step 3: If Edge(x, y) is a black pixel then
Step 4: Find the available relationships between two neighboring pixels,
Step 5: Compare the relationship values between two available relationships,
Step 6: Increase number of occurrence at the related cell in EDM2(x, y).

Algorithm for calculating the EDM_2

Step 1: Sort discerningly the relationships in EDM1(x, y).
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Step 3: If Edge(x, y) is a black pixel then
Step 4: Find the available relationships between two neighboring pixels,
Step 5: Compare the relationship values between two available relationships,
Step 6: Increase number of occurrence at the related cell in EDM2(x, y).

	135°	90°	45°	
	5	11	5	
180°	17	33	17	0°
	5	11	5	
	225°	270°	315°	

	135°	90°	45°	
	1	7	2	
180°	4	33	17	0°
	0	2	0	
	225°	270°	315°	

B. LBP Features

The Local Binary Pattern (LBP) operator is a more recent texture analysis technique that can be viewed as a statistical approach. It has been extensively accepted for both texture classification and segmentation due to its ease of use and efficiency in defining the local spatial structures of an image. Furthermore, it has been employed in a wide variety of computer vision applications.

The first version of the LBP operator takes into account a 3×3 neighborhood surrounding each pixel. The pixels with values higher or equal to the value of the central pixel are assigned a value of 1 and all those with values lower than the value of the central pixel are given a value of 0; in other words, each 3×3 neighborhood is given the threshold value of the central pixel. The threshold values are then multiplied by the binomial weights assigned to the corresponding pixels. The last step is the generation of the LBP code, which is used as a texture feature for the 3×3 neighborhood and involves adding up the values of eight pixels. Figure 8 shows how the LBP for each pixel is found.

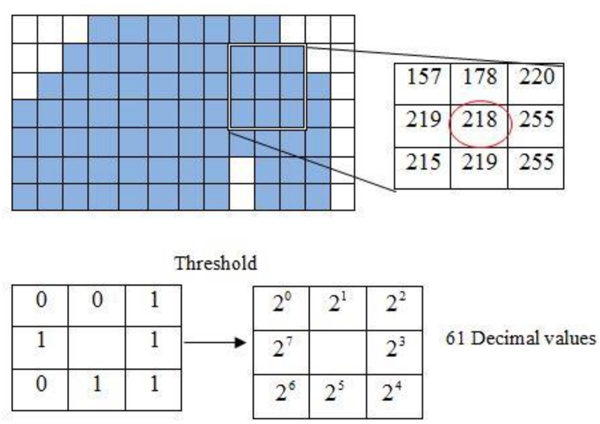

Figure 8. Find LBP for each pixel

The transformation of the binary code to a decimal value is achieved by assigning specific weights to the pixels belonging to the neighborhood in process, according to their position and by applying the following formula:

$$LBP = \sum_{i=0}^{p-1} bi \times 2^{i}$$

Where $b^{i} = \{0,1\}$ corresponds to the binary value of the binary image derived by applying thresholding.

VI. Results and Discussion

This paper described experiments conducted on this idea, and presents results and experiences that have been obtained in accordance with The proposed methods then we compare with two feature extraction for each of them and each one introduced to two classifier Multilayer Neural Network (MLNN) and Random Forest(RF).

The used of different dataset MPEG-7 CE-Shape-1 dataset for shape and calligraphy Arabic for texture were compared with the SIFT, GLCM-EDMS in order to assess their performance based on the previous methods SIFT, GLCM-EDMS [10].

The dataset has been split into training and testing datasets. In this experiment, the training dataset is determined from percentages between 60% and 70%. Based on the experimental results, the proposed method has obtained higher accuracy rates than GLCM-EDMS [10] and SIFT feature extraction methods in all experiments. Different percentages of training and testing data sets have been tested to determine the best performance.

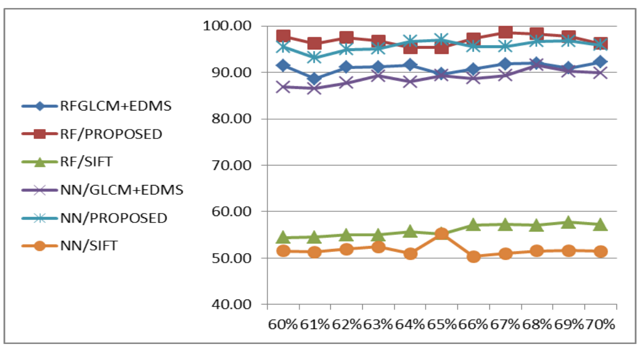

Figure 9. The classification results of the GLCM-EDMS, SIFT and proposed methods from 60% to 70% splitting of the training MPEG-7 CE-Shape-1 dataset and the classification results of neural network, Random Forest.

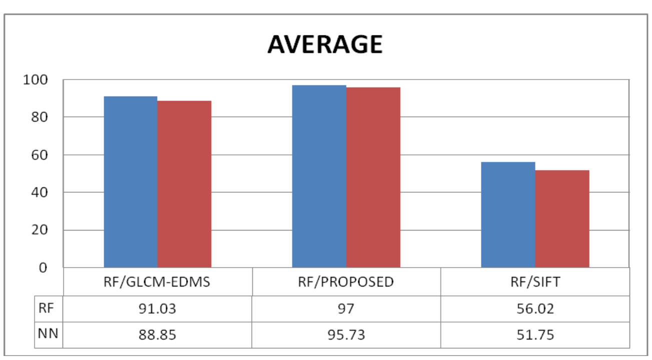

Figure 10: The average accuracy rates series of experiments on GLCM-EDMS, SIFT and PROPOSED using the MPEG-7 CE-Shape-1 dataset.

TABLE I. The ten experiments of the classification results of the 67% training sets with Random Forest using GLCM-EDMS, SIFT and Proposed feature extraction methods subsequently using the MPEG-7 CE-Shape-1 dataset.

Methods	GLCM-EDMS	SIFT	PROPOSED
exp#1	91.93	71.18	99.55
exp#2	93.72	70.67	99.06
exp#3	91.48	71.11	98.80
exp#4	93.27	71.54	99.70
exp#5	93.27	71.90	100
exp#6	93.27	72.35	100
exp#7	93.72	73.29	99.10
exp#8	92.38	71.62	99.55
exp#9	93.72	73.58	98.65
exp#10	92.38	71.98	99.55

This result for MPEG-7 CE-Shape-1 dataset will get to Mean and Standard deviation for the five experiments. Feature extraction is a significant factor in shape recognition, such as in the MPEG-7 CE-Shape-1 dataset. The global and local methods of feature extraction are the preferred methods for obtaining the best results.

TABLE II. The Mean and Standard deviation for the five experiments results for the GLCM-EDMS, SIFT and proposed methods using Random Forest classifier with MPEG-7 CE-Shape-1 dataset with 67% training.

Methods	***Mean***	***Standard Deviation***
GLCM-EDMS	91.96	1.20
SIFT	57.17	1.69
PROPOSED	98.76	0.51

The an above all figure and table for the first dataset call MPEG-7 CE-Shape-1 dataset for shape will explain for second dataset below.

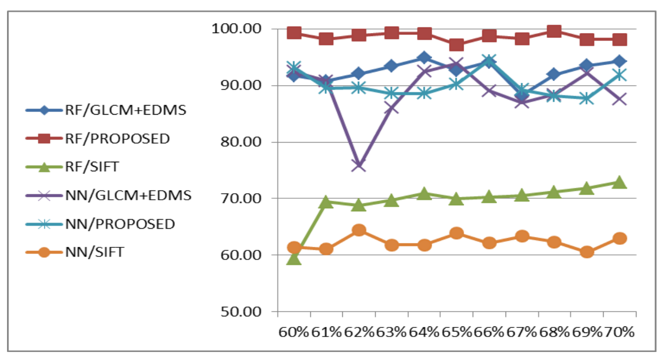

Figure 11. The classification results of the GLCM-EDMS, SIFT and proposed methods from 60% to 70% splitting of the training calligraphy Arabic and the classification results of neural network, Random Forest.

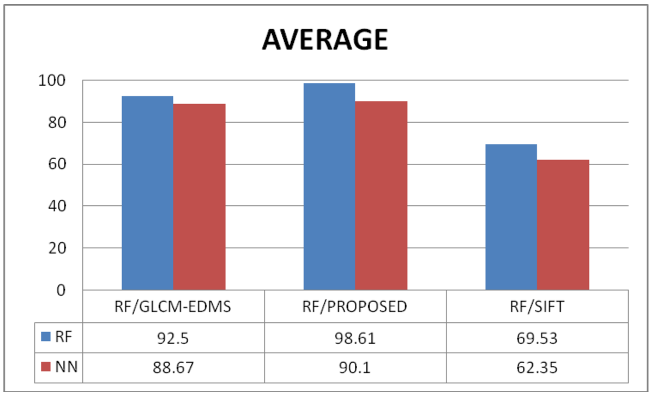

Figure 12. The average accuracy rates series of experiments on GLCM-EDMS, SIFT and PROPOSED using the Calligraphy Arabic dataset.

TABLE III. THE TEN EXPERIMENTS OF THE CLASSIFICATION RESULTS OF THE 68% TRAINING SETS WITH RANDOM FOREST USING GLCM-EDMS, SIFT AND PROPOSED FEATURE EXTRACTION METHODS SUBSEQUENTLY USING THE CALLIGRAPHY ARABIC DATASET

Methods	GLCM-EDMS	SIFT	PROPOSED
exp#1	91.84	57.21	98.59
exp#2	92.20	54.29	98.23
exp#3	92.91	56.49	99.29
exp#4	92.91	56.49	99.65
exp#5	90.49	55.59	97.88
exp#6	92.55	57.2	98.59
exp#7	93.26	56.65	98.94
exp#8	91.84	59.84	98.94
exp#9	89.36	59.25	98.94
exp#10	92.20	58.68	98.59

TABLE IV. THE MEAN AND STANDARD DEVIATION FOR THE FIVE EXPERIMENTS RESULTS FOR THE GLCM-EDMS, SIFT AND PROPOSED METHODS USING RANDOM FOREST CLASSIFIER WITH CALLIGRAPHY ARABIC DATASET WITH 68% TRAINING.

Methods	***Mean***	***Standard Deviation***
GLCM-EDMS	92.91	0.81
SIFT	71.92	0.93
PROPOSED	99.40	0.47

VII. CONCLUSION

This paper has addressed the problem of shape and texture pattern recognition which has been dealt with in previous studies on pattern recognition and texture analysis. It has proposed and implemented the statistical method of feature extraction. combine between the local and global feature extraction approaches were presented as well as the shape and texture analysis and a comparison between the different approaches. In the feature extraction phase, the LBP and EDMS features had been proposed. In the recognition phase, we had applied two classification techniques such as the Multilayer Neural Network (MLNN) and random forest. Based on the results obtained, it had proved that the proposed method had produced the best accuracy rate, compared with the SIFT and GLCM-EDMS.

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