# Evaluating face recognition with different texture descriptions and convolution neural network

**Wafaa Mohammed Saeed Hamzah Al-Hameed[1], Marwan B. Mohammed[2]**
[1]Department of Software, College of Information Technology, University of Babylon, Babylon, Iraq
[2]Department of Computer Science, Al-Nahrain University, Baghdad, Iraq

**Article Info**

***Article history:***

Received Sep 27, 2022
Revised Nov 15, 2022
Accepted Nov 23, 2022

***Keywords:***

Center symmetric LBP
Classic LBP
Convolution neural network
Face recognition
K-nearest neighbor

**ABSTRACT**

Extracting the remarkable attributes of the image objects is an issue of ongoing research special in the face recognition problem. This paper presents two directions. The first is a comparison between the local binary patterns (LBP) and its modified center symmetric LBP drawn from localized facial expressions and due to the efficiency, K-nearest neighbor (KNN) and the support vector machine (SVM) techniques play significant roles in this research used to implement the proposed system efficiently. The second direction proposes an efficient architecture by depending on deep learning convolution neural network (CNN) to implement face recognition. Such a design consists of two parts: a convolutional learning feature model and a classification model. The first one learns the important feature,while the second part produces a score class for each sample input. Many experiments are implemented on the known dataset once for the number of nearest neighbors (K value), and then decrease the number of expression samples for each individual the other time. The cross-validation method is used to provide a true picture of the accuracy of the face recognition system. In all experiment results, the center symmetric LBP with KNN outperforms the classic LBP. While significant progress in the results accuracy recognition ratio of the CNN model compared with other methods used.



***Corresponding Author:***

Wafaa Mohammed Saeed Hamzah Al-Hameed
Department of Software, College of Information Technology, University of Babylon
Babylon, Iraq
Email: wafaa2013saeed@yahoo.com and it.wafaa.mohammed@uobabylon.edu.iq

## 1. INTRODUCTION

It's known, that Biometric identification includes face recognition, voice recognition, retinal scanning, and fingerprint recognition and one of the most distinguishing aspects of the human body is the face. Persons can be identified using their faces [1]. A face recognition system is a computer program that can identify or verify a person using a digital image or a video frame from a video source. One method involves comparing selected facial traits from an image to a face database [2]. Face recognition is broken into four stages: detection, straightening, extraction of facial features, and matching or classification [3]. Face recognition technology seeks to mimic one of the natural human abilities: recognizing characteristics of faces in various contexts and connecting them with the knowledge stored in their memory. It is a simple and straightforward activity for humans, but it appears to be a difficult problem for computing systems due to a few natural characteristics such as face position, lighting condition, and the distance of the face from the camera [4]. Mostly, the common methods that were adopted in the face recognition system [5], [6] are those that depend on extracting algebraic properties [5] or geometric properties [7] or based on the concept of templet matching [8], or based on using artificial neural networks (ANN) [9] more of the database used for the scientific research purposes such as

(PUT, FERET, Yale, PIE, and ORL) to different people with different scale, position, and different facial expressions. Part of the set is used for training, and the other is used for testing.

The local binary pattern (LPB) has been selected here for feature extraction which is defined as the invariant measure of the texture which is derived from the texture definition of local neighborhoods. It is invariant rotation with respect to the domain of the image [10]. An extension of classic LBP is the CS-LPB which generates a small feature vector length through the negligence of information on the central pixels [11].

Many other methods then are developed for face detection and recognition, Vaillant *et al.* [12] applied the convolution neural network (CNN) to detect the face at the beginning, but great progress was made in the recognition of images [13]. In 2012 through the development of the convolutional neural network AlexNet which greatly improved classification accuracy on the Image Net dataset. LeNet-5 with a deep structure was proposed by LeCun [14], the structure consists mainly of an input layer, a convolutional layer, a pooling layer, and a fully connected layer, in addition to the output layer. The features of the convolutional layer are obtained from the local properties of the previous layer through the weights shared by the convolution. Then high-level features are categorized by fully connected layers. CNN simulates the biological visual perception system, where the perceptive cells receive light signals from the retina of the eye. At the same time, one cell does not receive all the signals, but only activates by sensing the stimulus in the stimulating area, so the visual space is generated by the superimposition of several cells. Edy Winarno and colleagues introduced a face recognition model in 2020 that employed a combination of form and texture vectors to generate fresh face images on 2D-3D reconstruction images. The reconstruction approach for obtaining 3D face images from 2D face images was carried out utilizing CNN method. Due Face identification utilizing 3D imaging has a disadvantage in that it is more sophisticated than face recognition using 2D imagery captured by regular cameras [15].

Due to the fast-growing CNN field, many researchers are attracted to provide reviews focused on several prospects and novel methods invented in this field. In Chen *et al.* [16] reviewed the attempts of researchers to exploit deep models to improve the performance of the recognition in the case of a single sample. This case is accrued in some practical situations when each entity has a single sample available for the training and the face recognition, in this case, is called single sample face recognition. Li *et al.* [17] are interested in presenting a review of the recent ideas that were put forward, not only two-dimensional convolutional but also one and multi-dimensional convolutional. The reviewing is considered the classic and advanced CNN models.

There are a lot of works that adopted the method close of our rapprochement like [18], [19]. For instance, the method proposed by Abaji and Salih [18] used wavelet, Eigenfaces, and Gray-Level Co-occurrence Matrix for data dimension reduction to improve the performance of face recognition by disregarding uninteresting features. similarity measurement is accomplished by using weighted Euclidean linear distance. The results illustrate the higher recognition rates when using the PCA and Wavelet in comparison with the GLCM method.

The computational efficiency of LBP, in addition, since it provides good support especially when the images have changes in the level of intensity, made several types of LBP used for face recognition purposes [20]: holistic LBP histogram (hLBPH), the spatially enhanced LBP histogram (eLBPH), holistic LBP Image algorithm (hLBPI) and decimated image window binary pattern (WBP)). All of these algorithms depended on the original LBP algorithm. They found that (hLBPI and WBP a) provide less computational complexity than the other.

Rahamathunnisa and Sudhakar [21] analyzed LBP with other methods (PCA and GLCM) used to extract features from the face image. The first method generates LBP descriptions, while PCA generates eigenvectors and eigenvalues, in addition to the GLCM method, which produces second-order statistical features. The methods were applied to newborn images with different expressions so that the extracted attributes are entered into the support vector machine (SVM) for classification. PCA method gives better accuracy results compared with other methods

Zangeneh *et al.* [22] presented a method based on the principle of the coupling mapping approach to recognize images of low intensity using DCNN. The basic idea is based on the use of two DCNN structures to transform low-resolution prob and high-resolution gallery images into a common space so that the distances between faces belonging to the same person are more fill than the distances from those belonging to different people. It is noticeable that two CNN were used to add more resources computations in order to obtain an optimal learned model parameter.

The authors tested the performance of the CNN with three face recognition methods: K-nearest neighbor (KNN), local binary patterns histog (LBPH), and principle component analysis (PCA) [19] by performing these methods on the ORL database. LBPH produces better results compared with (KNN, and PCA). On the other hand, it was found that the recognition process was accomplished using CNN with a better accuracy rate than the ratios of other methods. Especially those descriptions that are easy to compute and ensure high extra-class variance among different people in the case of face recognition and a little intra-class variance with respect to various changes of age, lighting, and other factors.

This research presents two contributions. The first proposed method summarizing the training set features group as well as the testing set on a two-dimensional matrix instead of a long feature when the method adopted divides the image into a number of regions so that the LBP feature histogram was computed for each region, which represents the contents of the texture within these regions, these histograms later will be integrated into a single histogram. Since of efficiency, KNN is used for classification based on the nearest distance of neighboring, so the voting is taken in order to predict the best class that fits the point [23]. So as the learning algorithm made correct predictions on the training set and the group is not part of the training set. So we need a measure that gives us an idea to correct classifier prediction. The cross-validation method was used to provide a true picture of the accuracy of the face recognition system.

The second proposed work is using CNN for face recognition. We assume a two parts design for the network represented by the feature learning part and classification model part so that the network receives the image, which in turn will pass through several stages (layers) ending with score class computation, which represents the class to which the face belongs

## 2. CLASSIC LBP

The simple method was firstly introduced by Ojala *et al.* [24]used to extract the LBP feature vector that can be characterized by a few steps. Figure 1 consist of three sub figures: Figure 1(a), Figure 1(b), and Figure1(c). These steps begin with dividing the image into non-overlapping cells (each cell of size 3* 3) as shown in Figure 1(a). Each central point for these cells is compared to its 8 neighbors, When the value of the central pixel is greater than its neighbor then set 1 else set zero value multiplied by powers of two and then summed to get the code for this cell as shown results in Figure 1(b). The Figure 1(c) display final result in binary and represented dicimal. The idea behind using the LBP features is that the face images can be seen as a composition of micro-patterns which are invariant with respect to monotonic grey scale transformations. Combining these micro-patterns, a global description of the face image is obtained [25].

| | | |
|---|---|---|
| 4 | 8 | 1 |
| 3 | 3 | 5 |
| 6 | 1 | 2 |

(a)

| | | |
|---|---|---|
| 1 | 1 | 0 |
| 1 | | 1 |
| 1 | 0 | 0 |

(b)

Binary: 11010011
Decimal: 211

(c)

Figure 1. The classic local binary pattern operator, (a) is (3*3) window, (b) is coding, and (c) is texture feature

The descriptor that describes the generation of the binary pattern is [26] as (1).

$$LBP = \sum_{i=0}^{P-1} \tau(m_i - m_c)^{2^i} \tag{1}$$

$$\tau(x) = \begin{Bmatrix} 1 & if\ x > T \\ 0\ , & otherwise \end{Bmatrix}$$

## 3. CENTER SYMMETRIC LBP

The center symmetric LPB (CS- LBP) is modified of the classic LBP that was assumed to get rid of the LBP problem which has a long histogram. The working principle of this update instead of comparing each adjacent pixel with the central pixel, the symmetric pairs of pixels of the center will include being compared, this process is described by the following (2) [27], [28].

$$CS = \sum_{i=0}^{\left(\frac{P}{2}\right)-1} \tau\left(m_i - m_{i+\left(\frac{P}{2}\right)}\right)^{2^i} \tag{2}$$

$$\tau(x) = \begin{Bmatrix} 1 & if\ x > T \\ 0\ , & otherwise \end{Bmatrix}$$

Where $m_i\ and\ m_{i+\left(\frac{P}{2}\right)}$ correspond to the gray values of center-symmetric pairs of pixels of P equally spaced pixels on a circle of radius R. In the case of using a center symmetric local binary pattern (CSLBP), Based on the center symmetric pixel difference, a local pattern is extracted from the input image pixels. Same as LBP, in CSLBP, each pixel is considered the center pixel. The difference of center symmetric pixels is calculated which is independent of the center pixel. Based on the difference, four binary numbers are assigned to the center pixel that is further multiplied by four weights and summed up to one value, which is called the center symmetric local binary pattern value. In a similar manner to LBP, the histogram is created for the feature vector of the CSLBP map [29]. Figure 2 describe the value of the center pixel with a relative of 8 neighborhood.

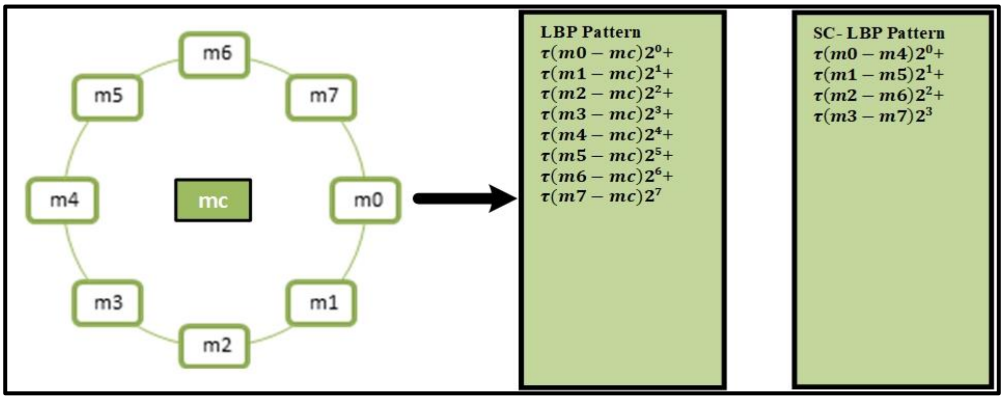



Figure 2. Classic LBP and center symmetric LBP local features for a window of 8 pixels

## 4. CONVOLUTIONAL NEURAL NETWORK

A CNN is an active algorithm that is quite compatible with image processing and pattern recognition [17]. In the case of using machine learning, the features map was extracted through a process called Handcraft features extraction, then the classifier is applied to solve a problem. Whereas the CNN automatically generates features and combines them with the classifier. The facility of the model depends on the number of different layers whose function is to transform the input data volume to the output data volume through the differential functions [30].

The deep learning architecture takes the input image and then assigns the importance of learned (weights and bias) to the various components of the image, and then classifies the image on the basis of these optimal learned model parameters, in other words, the power of the CNN is to learn the important properties necessary to identify the face image [31]. CNN consists of a group of layers, but the architecture in general consists of two main parts: the feature extraction (convolutional) model and the classification model. The image is passed to the convolutional model, which consists of several layers and is used as an attribute extractor by turning the image into an attribute vector. The classification model is linked to the attribute vector of the image and also consists of a group of layers. The goal of this part is to classify the input by combining the features that have been collected [32]. The model proposed to adopt a nonlinear activation function named rectified linear unit (ReLU). It is one of the common functions used in neural networks, especially in CNN as well as the perceptron. It produces 0 as an output when $x < 0$, and then produces a linear with a slope of 1 when $x > 0$. Thus, it is better than the sigmoid and the tanh activation functions that are explained mathematically in (3) [33]. While Figure 3 provides its visual representation of the ReLU activation function.

$$f(x) = max\ (0, x) \tag{3}$$

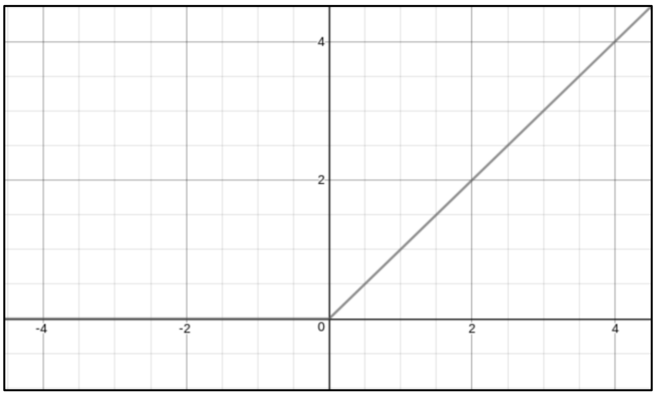



Figure 3. Rectified linear unit (ReLU) activation function

## 5. FIRST PROPOSED MODEL

This section introduces details of the proposed model. The main objective of this research is to evaluate the face recognition system through using remarkable feature results when applying the handcraft extraction method. And again, when using a convolutional neural network. As shown in the following sections:

### 5.1. Features extraction and recognition

As shown in Figure 4, at the start, the training and testing sets using the cross-validation method is prepared. In this way, the data is divided into segments $\{Seg_1, Seg_2, \ldots., Seg_n\}$, n-1 segments are used for training and one left out can be used for testing this is repeated many times (the first time $Seg_1$ is used for the test and the rest for the training, and the second time $Seg_2$ is used for testing and the rest is used for training and so on.

Then the feature vector characterizes the face image reserve row in the 2D dimensional matrix instead of the large dimension vector described by the long histogram as long as described in most of the previous research. This work summarizes the training set features group as well as the testing set on a two-dimensional matrix ($LBP_{MN}$), N denotes the number of non-overlapping image cells containing decimal values after bilateral conversion following application LBP method, M represents the number of images used either for training or testing. Detailed procedure for recognizing face using textures feature with K-NN technique as follows:

- Dividing each image into the number of non-overlapping windows size (3*3) then classic LBP and center symmetric LBP features are extracted.
- For the evaluation, the classification is implemented using KNN and SVM. The first (KNN) is a simple and non-parametric algorithm, non-parametric means that it does not make any suggestions about the distribution of data and there is no clear process of training (training developed very fast). KNN retains all data and the decision depends on the whole training data [34]. while the second (SVM) algorithm is a supervised machine learning utilized for classification. Each data item is seen as a point in n-dimensional space, n represents the number of extracted features and the classification is done by identifying hyperplanes that distinguish between classes [35]. The procedure of the face recognition system is charted in Figure 4.

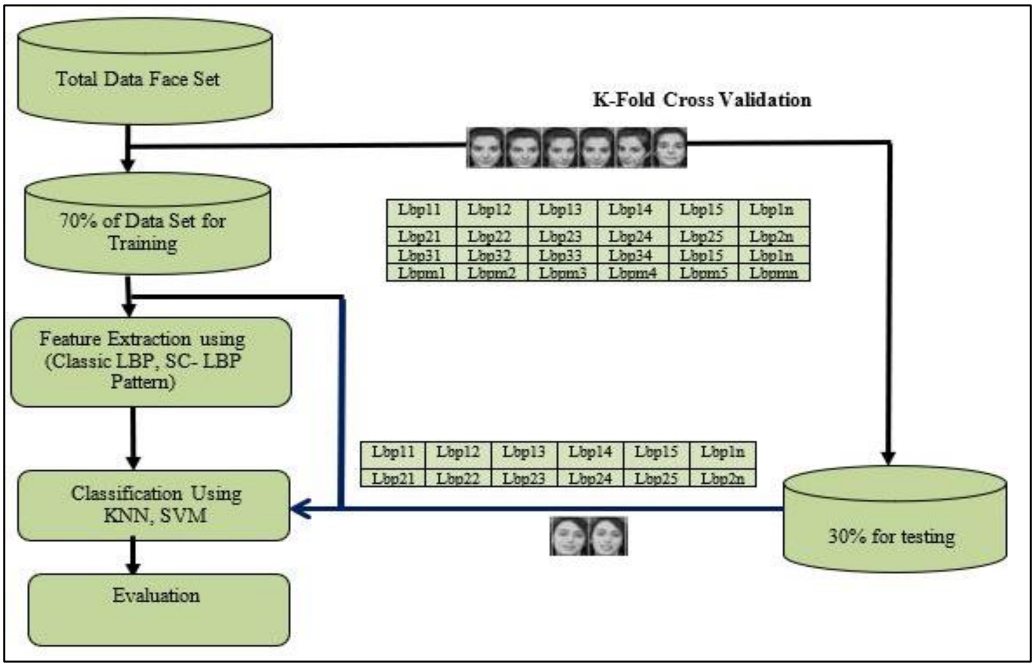



Figure 4. Face recognition using different texture features with different machine learning methods

### 5.2. CNN model for face recognition

The proposed CNN architecture Model is shown in Figure 4 used to distinguish faces. This architecture which consists of two main parts the model for learning the important features and the model for giving scores for each input sample. Each model includes many layers that perform different tasks:

#### 5.2.1. Feature learning model

– The first layer represents the input layer including raw pixels of the image received and stored for processing in the network. The image is resized to (64*64).
– The next layer is the convolutional layer with 24 filters where the kernel size is [3, 3], (padding =1), This layer is responsible for calculating the output of the nodes linked with the localized regions of the input image through the convolution process, the operation produces [64, 64, 24] feature maps while the parameters stride and padding specify the amount of information contained in each of these resulting feature maps.
– The (ReLU) layer follows the convolution layer, which adds nonlinearity to the network. This function leaves the size unchanged (64, 64, 24).
– The pooling layer then is used after that to implement the downsampling along the spatial dimensions. In this task, use the Max pooling (2, 2) with a stride size equal to 2 so that the activation maps spatial volume become (32, 32, 24).
– Also and again enter into the block of layers that re-implement the procedures from steps b to d but with the difference that the number of filters used is 48 to produce a number of features maps of the size (16, 16, 48).
– Then transform these dimensions into one dimension using a flatting layer Thus, the size has become (12288*1).

#### 5.2.2. Classification model

The final layer is a fully connected layer including fully-connected (Dense) layers. The first layer has 128 neurons, to add more non-linearity to the design that all nodes in this layer are linked to all nodes of the previous layer and the size becomes (12,288*128). While the second (last) fully connected used to generate a score for each class has 40 neurons equal to the number output of the network. The activation SoftMax function was used to standardize the network outputs so that they are confined between [0, 1] and these outputs indicate the probability of belonging to one of the 40 class labels. Figure 5 show the suggested CNN architecture models for face learning features and classification respectively.

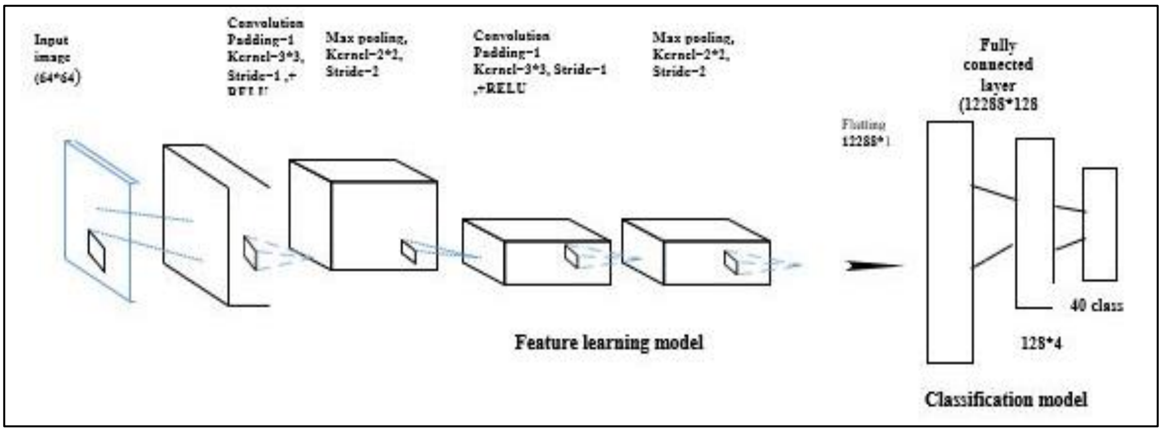



Figure 5. The proposed CNN architecture for the Face recognition procedure

## 6. RESULTS AND DISCUSSION

The Olivetti faces face database used for the experiments for this research consists of 400 samples for 40 person each person has 10 different expression images. These images are in gray level color and each one size is (1190*942) which is resized to [64*64]. Many experiments on the databases have been implemented to test and analyze our work, once with respect to the number of nearest neighbors (K value), and decreasing the facial expressions for each individual the other time. The samples of the images are shown in Figure 6 features of the local textures (LBP) computed stored for each class being used for comparison and recognition to input (query) images.

In the first proposed design experiment, the data set consisting of 400 samples for 40 individuals with 10 photos of different expressions, and different values of k (3,5,7,9) is executed. Table 1 shows ratios of accuracy and the best one is when k= 5. In general, decreasing the number of facial expression samples for each individual reduces the opportunity to find similarities among the points, as shown in Table 2.

Figure 6. Some typical original face images

Table 1. Recognition accuracy rates based on the LBP texture feature and KNN for 10 different expressions for each individual

| No. of k Nearest Neighbors) | Classic-LBP | Center-Symmetric LBP |
|---|---|---|
| K=3 | 97.4967 | 99.0267 |
| K=5 | 96.4133 | 97.2200 |
| K=7 | 96.2 | 97 |
| K=9 | 93.1933 | 95.1367 |

Table 2. Recognition accuracy rates-based LBP and KNN 5 different expression images for each individual

| No. of k (Nearest-Neighbors) | Classic-LBP | Center-Symmetric LBP |
|---|---|---|
| K=3 | 90.0900 | 93.4467 |
| K=5 | 93.2667 | 94.2800 |
| K=7 | 89.23 | 90.11 |
| K=9 | 85.9200 | 88.5033 |

For more comparison, another learning technique support vector machine is applied to observe its ability to distinguish 40 individuals (class). With 10 facial expression images for each individual. It's noticed that the KNN outperformed in terms of the recognition ratio as shown in Table 3.

Table 3. Recognition accuracy rates-based LBP using KNN, and SVM for 40 classes, 10 different expressions for each individual

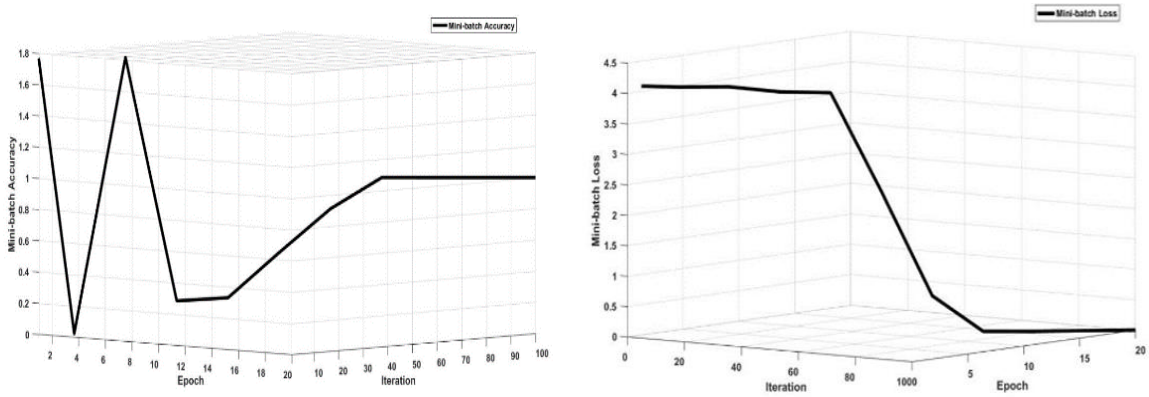
| Machine learning Technique | Classic-LBP | Center-Symmetric LBP |
|---|---|---|
| KNN (K=5) | 96.4133 | 97.2200 |
| SVM | 92.09 | 94.76 |

The second set of experiments has been conducted using the proposed CNN design for face recognition. The data has been split into two parts 320 with 80 samples for training and testing stages respectively using cross-validation to add more generality to the system. The performance of the CNN (accuracy ratio) of the model proposed was calculated and depicted in Table 4. We note the significant progress in the results of this model in the percentages of accuracy compared with other methods used.

Table 4. Best Recognition accuracy rates are based on different types of LBP using KNN (K=5), SVM, and proposed CNN architecture for 40 classes, with 10 different expressions for each individual

| Classic-LBP+KNN | Classic-LBP LBP+SVM | Center-Symmetric LBP+KNN | Center-Symmetric LBP+SVM | Proposed CNN |
|---|---|---|---|---|
| 96.4133 | 92.09 | 97.2200 | 94.76 | 98.2 |

The two parameters are Mini-batch accuracy and Mini-batch loss that describe the course of learning for the CNN proposed model as shown in Figure 7 by two subfigures: Figure 7(a) and Figure 7(b). The Mini-batch accuracy curve of the training process is shown for 20 epochs and 100 iterations that are performed during the learning process to obtain optimal model parameters as shown in Figure 7(a). We also note the Mini-batch loss decreased from 4.0997 to 0.0040 at the end of the 20 epoch, depending on the test results as shown in Figure 7(b).




(a) (b)

Figure 7. CNN parameters learning for (a) mini-batch accuracy and (b) mini-batch loss

## 7. CONCLUSION

In the scientific research on the problem of face recognition, a lot of research has relied on textures features such as LBP but the efficient method that we have done in this research is represented by the description of each region calculated using updated center symmetric LBP. These descriptions are not combined into a histogram as in previous works to decrease the dimension of the vector. Each Pattern value describes the appearance of the single region, and all the descriptions describe the general geometry of a whole image. We verify the accuracy in the case of using Classic-LBP and Center symmetric LBP with KNN and SVM, the center symmetric LBP outweighs center classic LBP. On the other side, the proposed CNN structure showed progress in comparison with the above methods in this faces recognition problem and is superior in the accuracy results through a deep learning algorithm that completely bypasses the handcraft features extraction stage. The complex structure can give more excellent results, but on the other hand, it can complicate the computational task. In addition, we need to test the system in case the data volume increases more and this will be our future work.

## REFERENCES

[1] M. Chihaoui, A. Elkefi, W. Bellil, and C. B. Amar, "A survey of 2D face recognition techniques," *Computers*, vol. 5, no. 4, p. 21, 2016, doi: 10.3390/computers5040021.

[2] K. D. Ismael and S. Irina, "Face recognition using Viola-Jones depending on Python," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 20, no. 3, pp. 1513-1521, 2020, doi: 10.11591/ijeecs.v20.i3.pp1513-1521.

[3] R. E. Saragih and Q. H. To, "A survey of face recognition based on convolutional neural network," *Indonesian Journal of Information Systems*, vol. 4, no. 2, 2022, doi: 10.24002/ijis.v4i2.5439.

[4] M. M. Hussein, A. H. Mutlag, and H. Shareef, "Developed artificial neural network based on human face recognition," *Indones. J. Electr. Eng. Comput. Sci*, vol. 16, no. 3, pp. 1279-1285, 2019, doi: 10.11591/ijeecs.v16.i3.pp1279-1285.

[5] Z. Jian, W. Zhi-ming, and Z. Ning, "Improved face recognition method based on deep learning," *Computer and Modernization*, no. 12, p. 90, 2019.

[6] Z. Xie, J. Li, and H. Shi, "A face recognition method based on CNN," in *Journal of Physics: Conference Series*, vol. 1395, no. 1: IOP Publishing, 2019, p. 012006, doi: 10.1088/1742-6596/1395/1/012006.

[7] M. O. Oloyede, G. P. Hancke, and H. C. Myburgh, "A review on face recognition systems: recent approaches and challenges," *Multimedia Tools and Applications*, vol. 79, no. 37, pp. 27891-27922, 2020, doi: 10.1007/s11042-020-09261-2.

[8] L. Tran, X. Yin, and X. Liu, "Disentangled representation learning gan for pose-invariant face recognition," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2017, pp. 1415-1424, doi: 10.1109/cvpr.2017.141.

[9] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, "Learning representations by back-propagating errors," *nature*, vol. 323, no. 6088, pp. 533-536, 1986, doi: 10.1038/323533a0.

[10] E. Prakasa, "Texture feature extraction by using local binary pattern," *INKOM Journal*, vol. 9, no. 2, pp. 45-48, 2016, doi: 10.14203/j.inkom.420.

[11] G. Xue, L. Song, J. Sun, and M. Wu, "Hybrid center-symmetric local pattern for dynamic background subtraction," in *2011 IEEE International Conference on Multimedia and Expo*, 2011: IEEE, pp. 1-6, doi: 10.1109/icme.2011.6011859.

[12] R. Vaillant, C. Monrocq, and Y. Le Cun, "Original approach for the localisation of objects in images," *IEE Proceedings-Vision, Image and Signal Processing*, vol. 141, no. 4, pp. 245-250, 1994, doi: 10.1049/ip-vis:19941301.

[13] R. Chauhan, K. K. Ghanshala, and R. Joshi, "Convolutional neural network (CNN) for image detection and recognition," in *2018 First International Conference on Secure Cyber Computing and Communication (ICSCCC)*, 2018: IEEE, pp. 278-282, doi: 10.1109/icsccc.2018.8703316.

[14] G. Wang and J. Gong, "Facial expression recognition based on improved LeNet-5 CNN," in *2019 Chinese Control And Decision Conference (CCDC)*, 2019: IEEE, pp. 5655-5660, doi: 10.1109/ccdc.2019.8832535.

[15] E. Winarno, I. H. Al Amin, S. Hartati, and P. W. Adi, "Face recognition based on CNN 2D-3D reconstruction using shape and texture vectors combining," *Indonesian Journal of Electrical Engineering and Informatics (IJEEI)*, vol. 8, no. 2, pp. 378-384, 2020, doi: 10.11591/ijeei.v8i2.1369.

[16] D. Chen, F. Liu, and Z. Li, "Deep learning based single sample per person face recognition: A survey," *arXiv preprint arXiv:2006.11395*, 2020, doi: 10.1007/s10462-022-10240-2.
[17] Z. Li, F. Liu, W. Yang, S. Peng, and J. Zhou, "A survey of convolutional neural networks: analysis, applications, and prospects," *IEEE transactions on neural networks and learning systems,* 2021, doi: 10.1109/tnnls.2021.3084827.
[18] M. A. Al-Abaji and M. M. Salih, "The using of PCA, wavelet and GLCM in face recognition system, a comparative study," *Journal of University of Babylon for Pure and Applied Sciences,* vol. 26, no. 10, pp. 131-139, 2018, doi: 10.29196/jubpas.v26i10.1848.
[19] P. Kamencay, M. Benco, T. Mizdos, and R. Radil, "A new method for face recognition using convolutional neural network," *Advances in Electrical and Electronic Engineering,* vol. 15, no. 4, pp. 663-672, 2017, doi: 10.15598/aeee.v15i4.2389.
[20] J. Olivares-Mercado, K. Toscano-Medina, G. Sanchez-Perez, M. N. Miyatake, H. Perez-Meana, and L. C. Castro-Madrid, *Face Recognition Based on Texture Descriptors*, IntechOpen, 2018.
[21] U. Rahamathunnisa and K. Sudhakar, "Analysis on texture feature extraction methods for face recognition in new born," in *2021 International Conference on Recent Trends on Electronics, Information, Communication & Technology (RTEICT)*, 2021: IEEE, pp. 894-897, doi: 10.1109/rteict52294.2021.9573777.
[22] E. Zangeneh, M. Rahmati, and Y. Mohsenzadeh, "Low resolution face recognition using a two-branch deep convolutional neural network architecture," *Expert Systems with Applications,* vol. 139, p. 112854, 2020, doi: 10.1016/j.eswa.2019.112854.
[23] D. Patidar, B. C. Shah, and M. R. Mishra, "Performance analysis of K nearest neighbors image classifier with different wavelet features," in *2014 International Conference on Green Computing Communication and Electrical Engineering (ICGCCEE)*, 2014, IEEE, pp. 1-6, doi: 10.1109/icgccee.2014.6922459.
[24] T. Ojala, M. Pietikäinen, and D. Harwood, "A comparative study of texture measures with classification based on featured distributions," *Pattern recognition,* vol. 29, no. 1, pp. 51-59, 1996, doi: 10.1016/0031-3203(95)00067-4.
[25] S. Wang *et al.*, "Content-based image retrieval based on improved rotation invariant LBP descriptor," in *2019 International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData)*, 2019: IEEE, pp. 1211-1216, doi: 10.1109/ithings/greencom/cpscom/smartdata.2019.00203.
[26] S. H. Khaleefah, S. A. Mostafa, A. Mustapha, and M. F. Nasrudin, "Review of local binary pattern operators in image feature extraction," *Indonesian Journal of Electrical Engineering and Computer Science,* vol. 19, no. 1, pp. 23-31, 2020, doi: 10.11591/ijeecs.v19.i1.pp23-31.
[27] R. P. Singh and P. Sharma, "Improving change detection using centre-symmetric local binary patterns," in *International Conference on Pattern Recognition and Machine Intelligence*, 2019: Springer, pp. 507-514, doi: 10.1007/978-3-030-34872-4_56.
[28] J. Xiao and G. Wu, "A robust and compact descriptor based on center-symmetric LBP," in *2011 Sixth International Conference on Image and Graphics*, 2011: IEEE, pp. 388-393, doi: 10.1109/icig.2011.32.
[29] M. Verma and B. Raman, "Center symmetric local binary co-occurrence pattern for texture, face and bio-medical image retrieval," *Journal of Visual Communication and Image Representation,* vol. 32, pp. 224-236, 2015.
[30] M. Jogin, M. Madhulika, G. Divya, R. Meghana, and S. Apoorva, "Feature extraction using convolution neural networks (CNN) and deep learning," in *2018 3rd IEEE International Conference on recent trends in electronics, information & communication technology (RTEICT)*, 2018: IEEE, pp. 2319-2323, doi: https://doi.org/10.1109/rteict42901.2018.9012507.
[31] M. Chaumont, "Deep learning in steganography and steganalysis," in *Digital Media Steganography*: Elsevier, 2020, pp. 321-349.
[32] I. Goodfellow, Y. Bengio, and A. Courville, *Deep learning*. MIT press, 2016.
[33] A. F. Agarap, "Deep learning using rectified linear units (relu)," *arXiv preprint arXiv:1803.08375,* 2018.
[34] K. Taunk, S. De, S. Verma, and A. Swetapadma, "A brief review of nearest neighbor algorithm for learning and classification," in *2019 International Conference on Intelligent Computing and Control Systems (ICCS)*, 2019: IEEE, pp. 1255-1260, doi: 10.1109/iccs45141.2019.9065747.
[35] S. Y. Chaganti, I. Nanda, K. R. Pandi, T. G. Prudhvith, and N. Kumar, "Image classification using SVM and CNN," in *2020 International Conference on Computer Science, Engineering and Applications (ICCSEA)*, 2020: IEEE, pp. 1-5, doi: 10.1109/iccsea49143.2020.9132851.


## BIOGRAPHIES OF AUTHORS

**Dr. Wafaa Mohammed Saeed Hamzah Al-Hameed** is an Associate Professor at the College of Information Technology, University of Babylon. She holds a Ph.D. degree in Computer Science with a specialization in AI and digital image processing. She is research areas are AI/Data mining, Text mining, and pattern recognition. She can be contacted at email: wafaa2013saeed@yahoo.com, or it.wafaa.mohammed@uobabylon.edu.iq.

**Marwan B. Mohammed** received her BSc in software engineering in 2008 from Baghdad College of Economic Sciences University and MSc in Computer Science in 2015 from Baghdad University, Baghdad, Iraq. he is an Assistant teacher in A.I. since 2015. Her research interests include artificial intelligence, natural language processing, security, and english texts. He can be contacted at email: marwan.badran@nahrainuniv.edu.iq.