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# Face Recognition Model Based on Covariance Intersection Fusion for Interactive devices

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Abstract— Face recognition has become more important recently than before. The objective of this study was to develop a face recognition model that can achieve high recognition accuracy. The better the extraction of features, the better results achieved. The already existing face recognition systems suffer from the problem of integration of different types of features. In this paper, a fusion feature-level face recognition method (FFLFRM) is proposed. The input face image is detected by applying the Haar-cascade method. After that, the features are extracted by using two statistical methods: local binary pattern (LBP) and principal component analysis (PCA). Then, the Covariance Intersection Fusion (CIF) technique is applied to integrate the LBP-, and PCA-extracted features. Afterwards, the integrated feature vector is input to a Multi-layer Perceptron Artificial Neural Network (MLPANN). Performance of the proposed method was tested using the Olivetti Research Laboratory (ORL) database of face images. To assess robustness of the proposed FFLFRM, it was applied on images with and without illumination and change in pose; and images with different expressions, occlusions, and levels of image resolution. For validation purposes, the proposed method was compared with a method applying LBP only, PCA only, and a combination of LBP and PCA with Frequency Partition (FP. Performance evaluation uncovered that the proposed FFLFRM has an average recognition accuracy of 96.75%. The recognition accuracy of this proposed method is quite good, particularly when compared with the corresponding accuracies reported by other studies that used the same face images.

Keywords- Feature Fusion; Covariance Intersection Fusion (CIF); Feature-Level; Face Recognition; Local Binary Pattern; Interactive devices.

## I. Introduction

Research on face recognition began in the late 1970s and has grown later into one of the most interesting and effective research domains in the field of computer science and information technology [1]. The face recognition system (FRS) is a computer application that identifies faces and automatically verifies them using their distinctive features [2].

These systems can be used for a variety of purposes in mobile and stationary interactive devices, including automated identity recognition, verification of criminal records, enhancement of the level of security by using surveillance cameras with the FRS, preparation in the event when a VIP is detected entering hotel, finding lost children by tracing and collection of photos taken by the cameras installed in public places, and identification of criminals in public places. Furthermore, they are used as an alternative to the use of a password because of the advantage which the face offers, being unique, thus eliminating the need for touching devices, which, in certain cases, can be medium of human infection. Actually, the FRSs can be used in different scientific fields [3], [4].

The FRS performs three major processes: face detection and image preprocessing, facial feature extraction, and face recognition [5]. At the stage of face detection and image preprocessing, the facial image is usually improved by removing the noise and the unwanted information from the scanned face in order to determine the exact location of the face in the image and identify its distinctive features [5]). In general, the face features in the image can be local or global. At the feature extraction stage, either type, or both types, of features can be extracted [6], [7]. Afterwards, the extracted features are categorized at the classification and recognition stage into a specific face using various machine learning classifiers such as the Support Vector Machine [8], the k-Nearest Neighbor (KNN) classifier [9], and the Artificial Neural Network [10].

However, there is a need for development of a robust face recognition system that best benefits from the features of the face. For that, one of the main challenges to recognition of faces is identification of specific and distinctive features of facial look that are stable against high differences in posture, lighting, and facial expressions, in addition to variations in image resolution [11], [12], [13].

Most of the existing FRSs use only one type of features, which does not give a complete representation of the face image. Moreover, for complex tasks like face recognition, review of the literature discloses that, in most of the time, a single method that is powerful enough to discover the entire classification information contained in a facial image was employed [11], [12], [13]. Hence, to overcome the challenges to enhance face recognition accuracy; there is an urgent need for development of recognition systems that employ methods, which incorporate distinctive face information into these systems.

Feature fusion combines different types of features, which may give a better representation of the face image. This, in its turn, can give an advantage to the recognition system by enhancing its performance. It can be implemented either at the feature extraction stage or the classification stage. At the feature extraction stage, different sets of features are merged into one compact set that is then used in the classification. If fusion is carried out at the classification stage, then different types of classifiers are due to be integrated for better accuracy [12], [14], [15], [16], [17]. The two main advantages of fusion at the feature extraction stage are (i) the ease of training since, in this case, only one stage of learning of the embedded feature vector is required; and (ii) enablement of utilization of the interrelationships among multiple features at an early stage because the feature fusion methods require normalization of the features [15], [17].

Based on the foregoing discussion, a FFLFRM is proposed here. This method is based on the Covariance Intercept Fusion (CIF) technique. In this model, global and local features of the face were extracted using Principal Component Analysis (PCA) and the Local Binary Pattern (LBP) method, respectively. After that, the embedded feature vectors were classified by using a Multi-layer Perceptron Artificial Neural Network (MLPANN). The proposed model was tested on 10,000 grayscale images taken from the Olivetti Research Lab (ORL) database of face images. For validation purposes, performance of the proposed FFLFRM was compared with levels of performance of other face recognition methods.

The remainder of this paper is organized as follows. The next section reviews literature on feature fusion methods in the context of face recognition. Afterwards, a description of the proposed FFLFRM is given in a separate section. Then, the experimental results are highlighted and discussed. Lastly, conclusions of this study and suggestions for future research are presented.

## II. Literature Review

Different types of approaches have been proposed in the literature for development of FRSs. In normal conditions, various approaches achieved high recognition accuracy. However, in other conditions such as change in pose, illumination, expressions, and low-resolution images the recognition accuracy decreases. Hence, there is a need for development of approaches that are robust against other than normal conditions. Some researchers focus on the recognition stage, at which confusion or deep learning methods were applied. Other researchers tried to enhance feature extraction by extracting different types of features to get better representation to the face. This results in either applying more than one classifier as hybrid approaches at the recognition phase, or merging different types of features into one confused feature vector. As such, recognition is implemented with one classifier only. In this paper, we specifically focus on research on face recognition using feature extraction and confusion techniques.

Image fusion is a method for combining appropriate information from two or more images into a single image [18]. The fused image should include human visual recognition and object perception. This method can be applied at the feature extraction stage or at the recognition stage [14]. So far, several fusion-based face recognition models were proposed for the recognition stage [8], [19], [20], [21], [22], [23], [24], [6], [25], [26]. At this stage, fusion is achieved after application of two separate classifiers in order to get the faces recognized on the basis of local individual features. Then, the classifiers are combined to make a final decision [15], [17]. Consequently, fusion at this stage includes integration of results of different classifiers [15], [17]. A proposed technique [22] applied LBP, pixel scores, and Gabor, then processed the outputs of all these classifiers together. Taigman et al. [27] used the same local descriptors, incorporating LDA-based, single-shot degrees of similarity. In another proposed method, Wolf et al. (2010) applied local descriptors with Gabor. Other researchers employed single-shot distance, Hellinger distance, rank-based distance, and two-shot distance for better recognition accuracy [28], [15].

At the feature extraction stage, fusion is carried out by extracting features and, then, combining them into one vector and conducting prediction by using a certain classifier [15]. A new method for texture classification that generalizes the LBP was proposed by [8]. In this method, two types of features are extracted from local patches. Performance of this method was tested on datasets picked from three databases: KTHTIPS2b, Outex, and CUReT. The best recognition accuracy was associated with the face images taken from the KTHTIPS2b dataset. In addition, this method gave quite similar results to those of other methods when tested on the CUReT dataset.

Sanderson et al. [29] developed a new technique in order to match images. Their technique has three main characteristics: (i) facial descriptors based on local features, (ii) use of sub-local measurements to compare different local regions, and (iii) shared learning of the most discriminative parts of the face and determination of the optimum mixing weights for combining scales. The proposed method was tested on datasets taken from the MOBIO, LFW, and PIE face databases. This method produced much better results than other techniques like the Kernel Affine Hull method and the Local Principal Angle method [29].

Tan and Triggs [12] suggested a system for facial recognition. At the feature extraction stage, two sets of features are extracted by the LBP and Gabor wavelet descriptors. The Kernel Discriminative Common Vector approach was then examined with vector-related features to derive distinct non-linear features for recognition. Performance of this system was evaluated on datasets drawn from several databases, including the FERET, FRGC 1.0.4, and FRGC 2.0.4 databases.

Ma et al. [30] proposed a new descriptor to identify persons based on the latest development of Fisher vectors. The descriptor they proposed consists of pixel coordinates whose accuracy was calculated for each pixel according to the two-person, re-identification standards of ViPer and ETHZ. The local descriptors were converted to Fisher vectors before being compiled for global image representation.

Yuan et al. [31] proposed face recognition model that is based on LBP and Local Phase Quantization (LPQ). In this model, the face image is divided into several different sub-images. Then, the LBP extracts the local features while the LPQ extracts the global features. After that, the LBP and LPQ features are incorporated into a vector that serves as a facial descriptor. Performance of this approach was tested on face images taken from the AR and YALE databases. Results showed that this technique has high efficiency and is more powerful than the methods that apply a single extraction method.

Gu and Liu [32] suggested a new LBP feature extraction technique which encodes local data and texture features. In this method, most of the features are extracted by Gabor wavelet. The k-nearest neighbor is then applied to the nearest pattern. Tests of performance of this method on face images picked from the FERET and BioID databases demonstrated the efficacy of the FLBP technique, which had better accuracy than other methods.

Li et al. [33] extracted different local features (e.g., LBP, SIFT, and densely-sampled image points) that had been generated by the Gaussian Mixture Model (GMM). Then, a SVM classifier was applied to link the contrasted vectors of the entire feature pairs so as to determine whether the face has, or has not, been recognized. Additionally, they proposed a combined Bayesian adaptation method for globally-trained GMM conditioning in order to better model the posture differences between the target face and similar faces. This method improves the face recognition accuracy. Its performance was tested on YouTube Faces Dataset and the so-called 'face in the wild (LFW)' dataset.

Vu [34] developed a new method based on revelation of the relationships among the directions of different local image structures and magnitudes of gradient. In addition, he introduced the new method of Patterns of Oriented Edge Magnitudes (POEM). Numerous experiments were performed on the FERET dataset, with both frontal and non-frontal images, and on the rather challenging LFW dataset. The experimental results confirmed that the proposed method has better efficiency than contemporary methods; it is less complex and has higher performance.

Mirza et al. [35] proposed a fusion system by integrating global and local features. In this system, the global features were obtained by applying discrete cosine transform (DCT) and PCA and the LBP was enhanced by two-dimensional DCT. Performance of this system was tested on the FERET dataset. The results showed that it has a recognition accuracy of 98.16%.

Tran et al. [36] proposed a new model which applies Local Ternary Patterns (LTP) and LBP for feature extraction. In this model, the face image is divided into a number of different sub-images. Then, the LTP and LBP features are sequenced into a single feature vector. Performance of this model was evaluated on the extended B-face database and the ORL faces database. The results of the experiments were promising.

Nusir [37] proposed a FRS for the feature extraction stage. The system uses the Frequency Partition (FP) method to integrate global and local features. It applies PCA to the global features and the LBP to the local features. Performance of this system was analyzed on the ORL database. The results showed an improvement in recognition accuracy in comparison with the case of integrating LBP and PCA in a single approach [37].

## III. Proposed Method

In this paper, a FFLFRM that uses the CIF method is proposed. This method has four main stages (Figure 1): face detection, feature extraction, feature fusion by CIF, and face recognition by MLP ANN. At the first stage, the Haar-cascade method is applied to detect the face based on its distinctive features, such as the nose, mouth, and eyes. Subsequently, the local features of the face image are extracted using LBP and the global features are extracted using PCA. The CIF is applied after that; at the fusion stage, as the local and global features are combined. Lastly, the generated feature vector is input to the MLP ANN at the face recognition stage.

### *A. Haar–Cascade Face Detection*

For face detection, Haar-cascade detection is performed. This method is a shape-based face examination method originally developed by Viola and Jones [38], [2], [13]. It classifies human activities (HAs) on the basis of HA-like properties [39]. In this research, Haar-Cascade is applied to determine the location of the face within the image by detecting its major parts such as the eyes, nose, and mouth.

### *B. Local and Global Feature Extraction Processes*

Feature extraction is the most important stage in face recognition and the recognition accuracy depends on efficient extraction of the optimum (i.e., most distinctive) features [13], [40]. By extracting the most distinguishing features differentiation between different face images becomes very easy [13], [40]. Two feature types to extract are global and local features. In the method proposed here; the FFLFRM, the LBP is applied to extract local features while PCA is applied to extract global features.

The LBP method is a statistical method that is commonly used to extract local features from an image. In 1996, Ojala et al. [41] improved it to be used in texture analysis. It works by taking a sub-image of certain size (e.g., 3x3) and locating the central pixel of each sub-image so as to calculate the feature values based on a pixel threshold. The local features are extracted first to be then combined with the global features at the next stage [41]. Typically, principal component analysis is the method used to extract features and reduce the dimensions of the image on the basis of the most distinguishing features. The PCA first computes the mean of the image matrix. Then, it calculates the covariance, the eigenvalues, and eigenvectors [42]. The main goal of PCA is to reduce the dimensionality of the data and exclude unrelated information that will not help much in distinguishing between patterns [43].

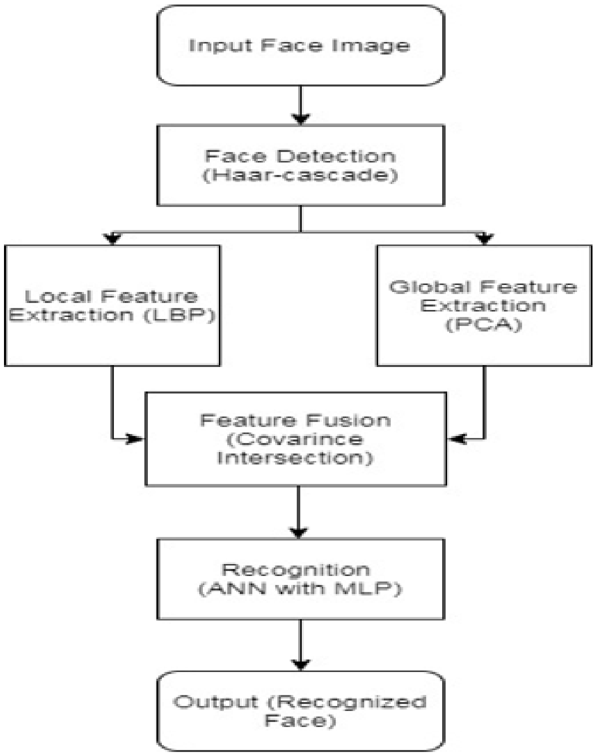


Figure 1. Architecture of the Proposed FFLFRM.

### *C. Covariance Intersection Fusion Technique*

The covariance intersection fusion method was developed in the mid 90's. It is used as a fusion technique that combines different types of features and integrates them into a feature vector [44]. What distinguishes the CI method from other fusion methods is that it takes into consideration cross-correlations of data. For that, this convex mixture gives consistent and accurate results. However, use of the covariance practically gives poor results [45].

In the proposed FFLFRM, the CIF technique is used to fuse the features extracted by PCA and LBP. The reason behind that is to obtain an image with greater resolution than the original image. After decomposition of the PCA and LBP features, the CI fusion rule is applied so as to obtain the fused image as illustrated in the following paragraphs.

The training images are converted into LBP and two-feature matrix PCA. The PCA is a two-dimensional matrix of rows representing the numbers of features and columns that represent the numbers of the trained images. On the other hand, the LBP is a three-dimensional matrix; two dimensions represent features and the third dimension denotes the number of the trained images.

Covariance intersection is achieved by first creating two matrices; an identity matrix, denoted I, and a matrix of zeros. Then, the trace of the LBP matrix is computed. Thereafter, a two-dimensional matrix, named X, is created with a size that is equal to the 'number of trained images – 1' times the 'number of trained images'. The values of X are calculated according to equations 1 and 2:

$$X(i,i) = Trace(i) \quad (1)$$

$$X(i,i+1) = -1 \times Trace(i+1) \quad where\ i = 1,2,\dots,n \quad (2)$$

Another one-dimensional matrix, named Y, is created with a size equal to the 'number of trained images' times 1. All values are zeros except the last value in the matrix. Then, a weighted matrix, W, is computed according to equation 3:

$$W = X/Y \quad (3)$$

Afterwards, a fused covariance matrix, named F, is calculated according to equation 4:

$$F = (W \times LBP)/I \quad (4)$$

### *D. Multi-Layer Perceptron Artificial Neural Network (MLP ANN) for Recognition*

The artificial neural networks in general have a variety of parameters to optimize that make them capable of fitting to different types of problems and performing hard and complicated tasks. In addition, they can handle different types of problems like approximation, classification, and prediction, and give good results [5], [46], [47], [48]. In this paper, the researchers applied the MLP ANN to the problem of face image classification. Accordingly, the confusion feature vector represents the network input layer. Five hidden layers and an output layer, representing the correct face recognized, are constructed. Details on construction and operation of the MLP ANN can be found in [5].

## IV. RESULTS AND DISCUSSION

In this study, the researchers propose FFLFRM with CIF. The classification results of this method are compared with results of a number of related previous studies. Of these, one is a face recognition method based on extracting local features that uses the LBP only. The second method only employs global features with PCA. The third method applies fusion based on LBP and PCA on the FP [37].

A robust face recognition method should always give similar results under different conditions. However, achievement of this target faces a number of challenges, including differences in the face images in poses, illumination, expressions, occlusion, and low resolution image [2], [49]. The MLP ANN was used in the proposed method and in the methods that are compared with in this study. Levels of performance of both the herein proposed model and some other methods were tested on 10,000 images of 40 different faces drawn from the ORL database. Each face image is of grey scale and has the size of 92x112 pixels. Results of comparison between these methods in performance based on the recognition accuracy are summarized by Table 1 and discussed next. Recognition accuracy is the number of correctly-recognized face images divided by the number of all the examined face images.

TABLE I. COMPARISON BETWEEN THE PROPOSED FFLFRM AND THREE FACE RECOGNITION METHODS IN RECOGNITION ACCURACIES

| Model | Pose change | Illumination change | Expression change | Low-resolution images | Occlusion |
|---|---|---|---|---|---|
| **Local based on LBP** | 95.15% | 95.27% | 96.24% | 95.06% | 95.75% |
| **Global based on PCA** | 95.3% | 95.81% | 96.99% | 95.46% | 95.55% |
| **Nusir (2018) based on FP fusion** | 97.02% | 96.47% | 97.73% | 96.99% | 96.18% |
| **The proposed FFLFRM** | 96.23% | 96.89% | 97.68% | 96.1% | 96.84% |

## A. *Pose Change*

Pose refers to the angle from which the image was approached. Different poses generate different scenes, which creates difficulties in matching the same features extracted from the same image [2]. In fact, the differences in poses make it hard to recognize the same face correctly and, accordingly, affect the overall recognition accuracy.

The recognition accuracies of the five compared methods that are associated with different poses are illustrated in Table 1 and represented graphically in Figure 2.

In terms of pose, Figure 2 shows that the proposed method has a recognition accuracy of 96.23% whereas the recognition accuracies reported for the other methods were 97.02%, 95.19%, and 95.3%, respectively. Thereupon, the proposed method performs better than the methods based on LBP and the method based on PCA. On the other hand, its recognition accuracy is only slightly lower than that of the model based on FP. The FP and CI are confusion methods that take benefit of LBP and PCA features together, thus resulting in a higher recognition accuracy. This confirms effectiveness of the proposed FFLFRM in face recognition under the condition of pose change.

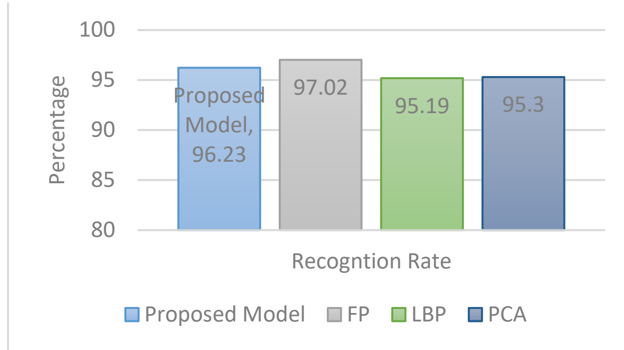


Figure 2. Comparison between the proposed FFLFRM and three face recognition methods in recognition accuracies as a function of pose change.

## B. *Illumination Change*

Illumination means that some place on the face has more light than the rest of the face [2]. This may make change in the face color that may affect the features extracted, which, in turn, negatively impact the recognition accuracy [50]. The recognition accuracy results associated with the proposed method and the other three methods under the condition of differences in illumination are shown in Table 1 and Figure 3.

Figure 3 underlines that the proposed FFLFRM had the best classification accuracy (96.89%). Meanwhile, the classification accuracies of the methods based on FP, PCA, and LBP were 96.74%, 95.27%, and 95.81%, respectively. On this account, performance of the herein proposed face recognition method is higher than that of the other methods. This emphasizes effectiveness of the FFLFRM in face recognition under the condition of differences in illumination. The reason why the model proposed here still results in higher accuracy with change in illumination is that the LBP method extracts features that PCA does not extract and vice versa, which are merged by CI fusion.

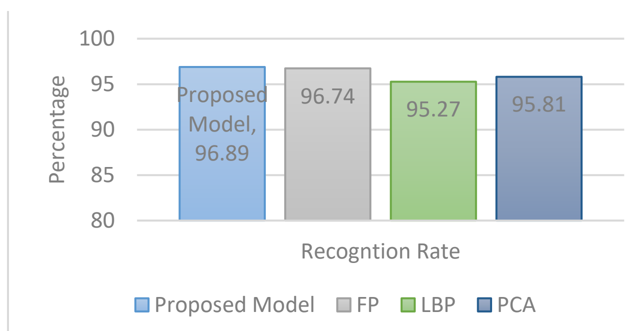


Figure 3. Comparison between the proposed FFLFRM and other face recognition methods in recognition accuracies as a function of differences in illumination.

## C. *Expression Changes*

Face expression indicates the shape and look which the face assumes to communicate feelings using such gestures as smiling, frowning, laughing, and crying [2]. Change in the normal face look to express such emotions results in differences in the features extracted from those of the normal face and influences the recognition accuracy.

The recognition accuracies concomitant with the proposed method and other face recognition methods under the circumstances of differences in face expressions are listed in Table 1 and depicted in Figure 4.

Figure 4 points out that the proposed method has a classification accuracy of 97.68% under the condition of different face expressions whereas the classification accuracies of the other methods are 97.73%, 96.24%, and 96.99%. The performance of the proposed method is better than that of the method based on the LBP and the one based on PCA and is nearly identical to accuracy of the method based on FP. This finding supports effectiveness of the FFLFRM in face recognition under the condition of different face expressions, knowing that other methods gave similar results due to the fact that change in expressions only changes the original face image slightly.

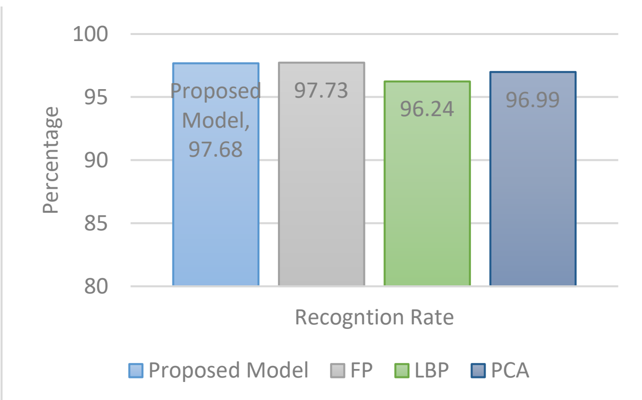


Figure 4. Comparison between the proposed FFLFRM and other face recognition methods in recognition accuracies as a function of differences in face expressions

## D. Low-Resolution Images

Image resolution describes the number of pixels in certain area (usually one inch) of the image. Low resolution occurs due to several factors such as type of the camera used and some environmental conditions [2]. In general, the recognition accuracy may be severely impacted when the input images are of low resolution. The recognition accuracies of the proposed method and the other methods under the circumstance of low image resolution are given by Table 1 and represented graphically in Figure 5.

Figure 5 points out that the proposed method has a recognition accuracy of 96.1% whereas the recognition accuracies of the other methods are 96.99%, 95.06%, and 95.46%. As such, the performance of the proposed method is better than that of the method based on the LBP and the one based on PCA but only slightly lower than that of the method based on FP. This stands as evidence in favor of effectiveness of the FFLFRM in face recognition under the condition of low image resolution.

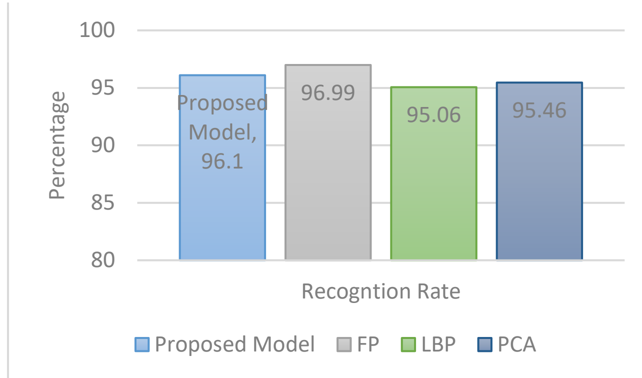


Figure 5. Comparison between the proposed FFLFRM and other face recognition methods in recognition accuracies under the circumstance of low image resolution.

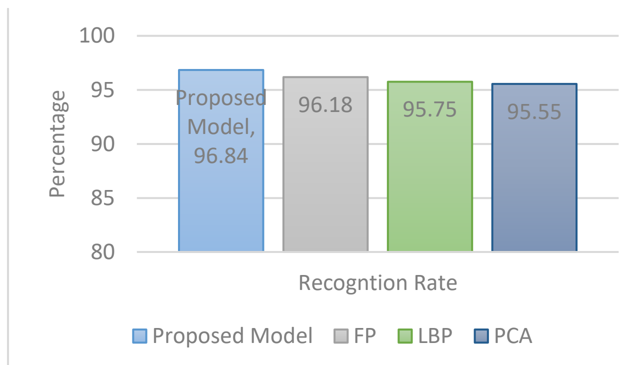


Figure 6. Comparison between the proposed FFLFRM and other face recognition methods in recognition accuracies under the condition of presence of occlusion.

## E. The Occlusion Challenge

Image occlusion describes the case when some part of the face image is covered. The covering may be due to an intrusion while taking the picture or a result of the subject being wearing such things as mask or sunglasses, which usually hide part of the face [2]. The face recognition accuracy may be detrimentally affected by covering of part of the face as some features will, accordingly, be missing or not extracted successfully.

The recognition accuracies of the method proposed here and the other methods under the condition of presence of occlusion are presented in Table 1 and Figure 6.

Figure 6 brings to surface that the proposed FFLFRM had the highest recognition accuracy (96.84%). The recognition accuracies of the rest methods were 96.18%, 95.75, and 95.55%. Therefore, performance of the proposed method is better than that of any of the other methods compared with in Figure 6. This shows that the proposed FFLFRM is robust against the occlusion challenge. It is noticed use of the LBP produces higher recognition accuracy than use of PCA. It seems that occlusion of part of the image affects performance of PCA negatively because it is a global method that takes the image as a whole. Thus, its performance with the LBP drops because the latter deals with each piece of the face image independently.

## V. Conclusions and Future Directions

Face recognition is an interesting topic as life style is changing these days and there is growing production of applications and services that are used without touching the related devices, especially under the conditions of epidemics and communicable diseases. By enhancing the accuracy of identifying the human face, further applications that rely more on face recognition techniques than on other pattern recognition techniques are developed because of the ease of their use and their lower requirements. Fusion of features is one of the techniques, which contribute to development of face recognition systems owing to that they can merge and normalize different local and global features and take advantage of differences between them. The fused features can then constitute an input for the face recognition stage.

In this paper, a FFLFRM based on the CIF technique has been proposed. This proposed method applies Haar-cascade face detection and employs LBP for extraction of local features and PCA for extraction of global features. Then, the CIF method is applied to merge both feature types extracted by LBP and PCA. Lastly, the method employs the MLP ANN for face recognition.

Performance of the proposed method was tested on 10,000 face images drawn from the ORL database. The recognition accuracies under the conditions of differences in pose, illumination, and expressions, as well as low image resolution and presence of occlusion, were 96.23%, 96.89%, 97.68%, 96.1%, and 96.84%. These recognition results are good, especially when compared with the results produced by other methods under the same conditions. The proposed method and the other methods compared with were all tested on images taken from the ORL database (Table 1).

In view of the study results, the researchers conclude that applying feature fusion in the feature extraction phase enhances the recognition accuracy. It allows for benefiting from the different types of features that can be extracted. Our approach is limited to two-dimensional images. Related future research may examine the face recognition accuracy when other fusion methods are used and test their performance on both two-dimensional and three-dimensional face images. In addition, other feature extraction methods than LBP and PCA may be evaluated, including methods that extract structural features. Moreover, performance of the proposed method can be assessed when appropriate classifiers (e.g., the HMM and SVM) are employed.

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