A Novel Feature Extraction Based Person Recognition Using Local Phase Quantization and Geometric Features

P Karuppanan (karuppananp21@gmail.com)
Pandian Saraswathi Yadav Engineering College https://orcid.org/0000-0002-4179-0163
K. Dhanalakshmi
PSNA College of Engineering and Technology

Research Article

Keywords: Face recognition, criminal identification, Local Phase Quantization (LPQ), Directional Graph Convolutional Neural Network (CNN)

Posted Date: March 23rd, 2021

DOI: https://doi.org/10.21203/rs.3.rs-197646/v1

A NOVEL FEATURE EXTRACTION BASED PERSON RECOGNITION USING LOCAL PHASE QUANTIZATION AND GEOMETRIC FEATURES

*[1]P. Karuppanan, [2]K. Dhanalakshmi

*[1]Assistant Professor, Department of Computer Science and Engineering, Pandian Saraswathi Yadav Engineering College, Sivaganga, India.

[2]Professor Department of Computer Science and Engineering, PSNA College of Engineering and Technology, Dindigul, India

*[1]Corresponding Author: karuppananp21@gmail.com

Abstract—

At present, it is simple for everyone to generate digital pictures of their routine life and use them for different purposes. Similarly, facial recognition is a trending technology that can identify or verify an individual from a video frame or digital image from any source. There are numerous techniques involved in the working principle of facial recognition. But the simplified method is feature extraction by comparing the particular facial features of the images from the collected dataset. Multiple algorithms are existing for feature extraction, but they fail to give high accuracy. The proposed algorithm based on deep learning provides a high recognition rate by using a convolutional neural network for classification. For feature extraction, Local Phase quantization, Geometric-based features, and directional graph-based methods are implemented. Various performance metrics, such as recognition rate, classification accuracy, accuracy, precision, recall, F1-score is evaluated. The proposed method achieves high-performance values when it is compared with other existing methods. It is mainly developed to calculate the casual visit of a person to the mall, and it is also deployed for criminal identification.

Index Terms— **Face recognition, criminal identification, Local Phase Quantization (LPQ), Directional Graph Convolutional Neural Network (CNN)**

I. Introduction

Face recognition can also be defined as biometric artificial intelligence relied on the application that is exclusively designated to recognize a person by exploring sequences based on the individual's facial shape and texture. Even though facial recognition has a wide variety of applications, it is typically essential to use it in the detection of criminal and forensic investigations and inquiries. Applying the digital images for the identification of victims can be challenging at specific occasions. Especially when the individual is wearing a mask or tattoo, or if the environment has background noises, camera distortion, insufficient storage, inadequate computing techniques, occlusion, detection of identical images and low-resolution images(Dutta, Gupta, & Narayan, 2017).

The impression of face recognition is to provide a computer to identify and analyze the human face in a fast way with high precision. Many algorithms are developed to improve its accuracy. Nowadays, deep learning explored the hidden sights of advanced computing applications and executed it in the right place to get an efficient expected output. It is trained similar to the human brain to analyze multiple human faces and store it in a database for future use. Generally, human utilizes all his sensory organs to recollect and analyze the input data, a similar computer process, and the input captured images into various features by a different algorithm. To get the exact desired result and confirm it by comparing it with the original picture by an integral section of biometrics and matching of essential traits. The system involved dual methods, such as face detection and face recognition(Amos, Ludwiczuk, & Satyanarayanan, 2016). Face detection is used to search and find one face by image processing, and face recognition is performed by comparing and analyzing the processed image with similar images from the database.

The method of face recognition in the proposed research comprises feature extraction and feature classification methods. In feature extraction, Phase quantization, directional graph-based process, and Geometric based feature extraction are performed. The feature classification is achieved by using convolutional neural networks for criminal identification. The mandatory methods for effective facial recognition should calibrate the facial expression from the given images. The facial expression can be derived from eyes, mouth, eyebrows, cheeks, and it's represented as salient regions. But few emotions like surprise and sadness acquired with only one salient feature, but

anger and fear cannot be obtained from a single salient feature. So feature extraction of the image is mandatory to extract the actual property of the pictures.

In feature extraction, Phase quantization is applied to extract the features from blurred images by short Fourier transform to analyze the structural properties of the image with promising values of accuracy and efficacy(Xiao, Cao, Wang, & Li, 2017). Directional graph-based and geometric based methods in feature extraction are applied to extract the facial feature in ROI along with error filtering techniques to provide prominent face components. It is used to locate the edges and relative size and position of mandatory expression components such as mouth, eyes, nose, and eyebrows. Then it is differentiated into the unimportant and meaningful part and also the conversion of grayscale distribution into feature vector based on the value of the pixel. The feature extraction is based on image pixel distribution, orientation selectivity, and spatial localization. The extracted images are then fed into CNN for further classification by deep learning. It is composed of multiple layers to detect necessary edges, intricate shapes, and by further processing, the final layer can catch the entire face and confirm it by verifying with the high dimensional dataset. Hence it is mostly preferred in real-time applications.

Face recognition is also based on the biometric aspect, which comprises the advantages of high precision and low intrusion in a program that utilizes an individual's face to spontaneously detect and authenticate the individual from a digital picture from any source. It compares the chosen facial attributes from the image and faces the repository database, or hardware can also be employed to authenticate an individual. It is mainly deployed in genetic engineering and biometric devices for identification, authorization, verification, and authentication.

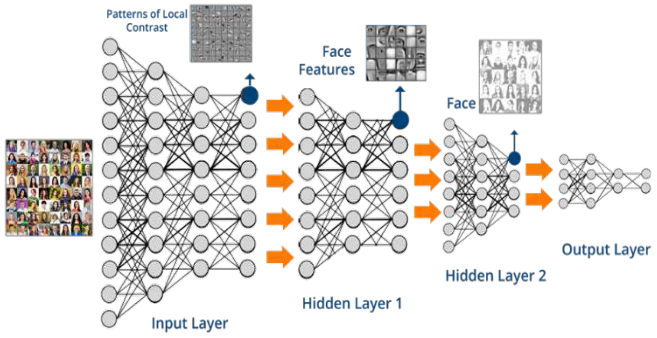

Fig 1- Schematic diagram of Convolutional Neural Network

Many companies have adopted face recognition for security purposes by implementing CCTV to manages and control the organization. Apart from security system, it have other exciting applications such as unlocking the phones, more refreshing advertising, finding missing people, protecting the law enforcement, identifying person on social media, diagnosing various types of diseases, spotting VIP at events, protecting school and government institutions from threat, and controls the access to sensitive regions.

A. The Objective of the research

- The applied machine learning algorithm, such as Local Phase quantization and Geometric based feature extraction, gives increased precision values when compared to other existing methods in-person recognition techniques.
- To find the optimal path to achieve the best features using directional graph-based features.
- The proposed research using novel Convolutional Neural Network can be employed as an effective classifier and applied in the real-time dataset for criminal identification.

B. The Organization of the research

The organization of the research is as follows. Section II explains the related work of face recognition on different feature extraction and classification methods. Part III is based on the detailed description of the proposed work. Section IV represents the analysis of the performance of the proposed method, and section V concludes the results of the research work and explains its future extension of the work.

II. REVIEW OF EXISTING TECHNIQUES

In modern ages, face recognition has achieved extensive attention from research and market, but still, it has some challenging task to implement in real-time applications. In past decades, a wide variety of face recognition machine algorithm is developed. But the proposed techniques in feature extraction and classification achieves high accuracy in face recognition. The paper is based on CNN in an image recognition process for the input of the Gait energy picture. It is composed of dual pattern trios' images of pooling, convolutional, and normalization cover and double connected layers with high efficacy. This method involves silhouette extraction, extraction of features, and matching of images(Kamencay, Benčo, Miždoš, & Radil, 2017). The silhouette extraction is made to avoid being affected by clothing, texture, and color. Then the GEI picture is fed into CNN of 88*128 pixels.

The face recognition method involves face area acquisition, localization, and segmentation to define the facial expression, face shape, and position of components, and the quality of the image(Laiadi et al., 2018). Then feature detection and

extraction of the face are obtained by geometric approach by designing feature vectors to locate the corners of the various face feature components. Then it is fed as the input image for the back propagation neural network model for facial expression recognition. But this method fails to work if there is any alteration in eye areas.

The link prediction in face recognition is divided into two types, such as feature extraction and feature learning methods. Similarity-based methods, probabilistic methods, and likelihood-based methods fall under feature extraction techniques. In similarity-based models, it follows global, local, and Quasi-local approaches by calculating the similarity between nodes. Depending on the structure of the network, a statistical model is designed to calculate the possibility of unnoticed connections to happen by using maximum likelihood models such as Hierarchical structural design and stochastic block model. These techniques are time-consuming and derive an accurate result. In feature learning methods, CNN extract features from the graph to check the connection between linked nodes and extract the data from the topology of the system(El Khiyari & Wechsler, 2017). The awareness of this learning model is to establish the structure of the localized neighbor by disintegrated feature data as an alternative to creating the entire graph by multiple source link prediction of input images.

The detection and localization of blurred face using local phase quantization applying Fourier transform phase in resident neighborhoods(Wechsler & El Khiyari, 2018). Under certain conditions, the period can be represented as a blur invariant attribute. So in the analysis, a histogram of local phase quantization labels calculated in resident areas is executed as face descriptor, related to broadly applied local binary pattern for a description of face images. But to limit the impact of lighting alteration in face pictures, procedure on illumination normalization is applied that comprises of contrast equalization, gamma correction, and Gaussian filtering that increases the result of recognition accuracy.

Some investigations made on a pair of parent and child to verify the effectiveness of the local phase quantization. The standardized and cropped images of parent and child were fed as input and converted to grayscale. Then local phase quantization is applied to retrieve the local features of every mode(Garg & Kaur, 2016). Encrypted images are differentiated into k non overlap rectangle scratches, and histogram values define each stretch. Each histogram has allocated to the high dimensional feature vector. Then cosine similarity is analyzed between the images by projecting into transformed subspace, and the resultant score is compared with threshold value from ROC by performance measures. With the obtained result, it is decided whether the person belongs to the same family or not.

The face is an essential attribute considered in a security system. Even though it is applied vastly, there is some limitation such as illumination, pose, and condition of the pictures(Ghimire, Lee, Li, & Jeong, 2017). To overcome this issue, face recognition is performed under non-uniform illumination by CNN that can learn exclusively local patterns from information is utilized for identification of a face. The symmetry of face data is processed to eliminate and enhance the performance of the system by accepting the horizontal reflection of the face images. The experiment was made using the Yale dataset under various illumination settings and showed moderate enhancement in the performance of CNN. The production remains undisturbed by the horizontal reflection of images. But it is failed when it is applied with fisher discriminant analysis and fisher linear discriminant analysis that is based on Gabor wavelet transform.

Human gait is soft biometric that support to identify an individual by their walking gestures(C. Li, Min, Sun, Lin, & Tang, 2017). To enhance performance recognition, the video-based sensor is applied by using convolutional features. The depth gait is introduced by applying a pre-trained deeper network dataset without any apt tuning. It is performed by the integration of more soft biometric attributes by the stochastic model. The height and stride length is considered as input information for the gait recognition system and improves its performance. But the stochastic model has some issues in weighting computations in calibrating the score of soft biometrics. Hence the model comprises the bunch framework of gait feature extraction, Gait score estimation, estimation of soft biometric trait, and probabilistic smooth biometric system. The combined score is delivered from the probabilistic system.

The gender-based classification is also made possible using a supervised machine learning approach. The diverse classifier used in this approach is the support vector machine, convolutional neural network, and adaptive boost algorithm. The input images are fed into pre-processing for removing noisy information, and feature extraction is based on a geometric approach to extract meaningful data from the processed images. It is fed into the combination of a classifier to get the resultant output. It is used to recognize the gender of the picture.

III. PROPOSED METHODOLOGY

This section explains the proposed work of the research. The features from the image are extracted using Local phase quantization and geometric based features and classified using novel based convolutional neural network. It is executed in a shopping mall to identify the individual to evaluate the person's number of visit to that mall.

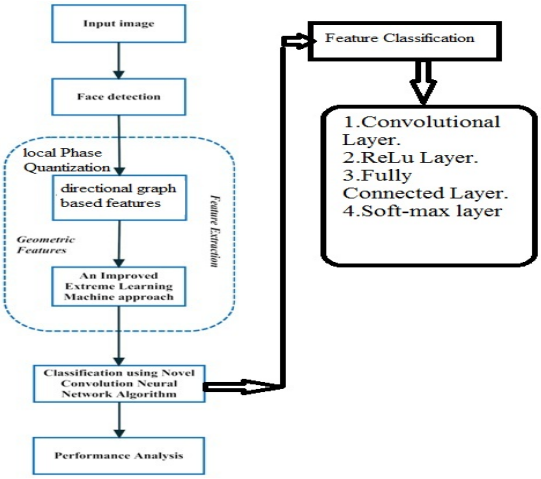

Fig 2 – Architecture of the proposed system

A. Feature Extraction

In general, Local Phase quantization is insensitive to centrally symmetric texture images. So this research considered both spatial and temporal coordinates. In statistical analysis, to overcome the loss of generality, the covariance matrix and cross-correlation are evaluated for the transformed coefficients.(Xiao et al., 2017)

This method is based on the property of blur invariance of the Fourier phase spectrum. It utilizes local phase data that is derived using a two-dimensional discrete Fourier transform or Sort-Term Fourier Transform(STFT) calculated on a rectangular matrix M × M at each pixel position x of image f(x). It can be formulated as below equation 1,

$$F(q,a) = \sum_{b\in N_a} f(a-b)e^{-j2\pi q^T b} = w_q^T f_a \qquad (1)$$

Here, w_q represents the basis vector of frequency q.

f_a Vector represents all image samples from neighborhood N_a.

Local Phase quantization is defined as follows,

- The original image is compared with the input image, and it is formulated as follows,

$$g(a,b) = f(a,b) \otimes h(a,b) + n(a,b) \qquad (2)$$

Where $h(a,b)$ is represented as a Point Spread Function (PSF),

$n(a,b)$ Is described as an additive noise

- Then the Fourier transformation is performed to convert the image from the range of high intensity to low intensity. It is formulated as below,

$$G(m,n) = F(m,n).H(m,n) \qquad (3)$$

Where $G(m,n), F(m,n), H(m,n)$Fourier are transforms of $g(a,b),\ f(a,b),\ and\ h(a,b)$ respectively.

- In order to predict the intensity range of an image, phase information and magnitude can be extracted as follows,
-

$$\angle G(a,b) = \angle F(a,b) + \angle H(a,b) \qquad (4)$$

Where $\angle G(a,b), \angle F(a,b), \angle H(a,b)$ are phases of $g(a,b),\ f(a,b),\ and\ h(a,b)$ respectively.

- To analyze the impulsive response of an image, Point Spread Function is calibrated as below,

$$\angle H(a,b) = \begin{cases} 0, & if\ H(a,b) \geq 0 \\ \pi, & otherwise \end{cases}, \qquad (5)$$

To calculate the relative translation between two pixels, phase correlation is estimated as below,

$$\angle G(a,b) = \angle F(a,b), \text{ for all } H(a,b) \geq 0. \qquad (6)$$

Then, Short Term Fourier Transform is executed at first to extract phase information for every pixel. It can be calculated as below,

$$G(a,b) = \sum_{a\in N_b} \sum_{b\in N_b} g(a,b) e^{\frac{-j2\pi(ma+nb)}{M}} \qquad (7)$$

The final results are organized as below,

$$V = [G(m_1), G(m_2), G(m_3), G(m_4)] \qquad (8)$$

And

$$W = [Re\{V\}, Im\{V\}] \qquad (9)$$

Where $Re\{V\}, Im\{V\}$ represent real and imaginary parts correspondingly.

Finally, the distribution histogram of the encoded values x within the image is constructed to yield local phase quantization in 256 dimensions. It is formulated as below

$$x = \sum_{i=1}^{8} q_i 2^{i-1} \qquad (10)$$

Where q_i, the quantization of the ith element in W is given by,

$$q_i = \begin{cases} 1, & if\ W_i \geq 0 \\ 0, & otherwise \end{cases} \qquad (11)$$

$$G_a = V^T F_a \sum_{i=0}^{N-1} f(i) g(a,b) \qquad (12)$$

Although local phase quantization quantizes the coefficients of short term Fourier transform, this process tends to ensure blur-insensitivity, but somewhat loss discriminative power. It is only the sign of the STFT coefficients that affect texture characterization.

B. Directional Graph-based Features

In this process, the input image is represented as a graph where each pixel in the picture is mapped as times series of respective vertex(Mutlu & Oghaz, 2019). Here the concept of image retrieval process is based on the graph theory, and edge detection is performed instead of standard map-based representation. The main focus of edge detection is to capture the rapid changes in image brightness.

The representation on the graph-based method enables direct access to edge nodes of the picture without any segmentation and search of edge points as performed in map-based representation

Another advance is less data consumption; only data for nodes and their connections are needed, which is important in large database applications for good scalability.

Typically, a time series $\{x_i\}_{(i=1,\ldots,n)}$ is mapped into a graph $G(V,E)$ where a time

Point x_i is mapped into a node $v_i \in V$.

The relation between any two points (x_i, x_j) is represented as an edge $e_{ij} \in E$, and the value is defined as below,

$$e_{ij} = \begin{cases} 1, & x_k < x_i \wedge \ x_k < x_j \quad \forall k \in (i,j) \wedge i < j \\ 0, & otherwise \end{cases} \tag{13}$$

Where e_{ij} implies the presence of edge.

If $e_{ij} = 0,$ implies that the edge does not exist.

There are several steps in assessing directional graphs, which are explained further.

Construction of Directional graph:

Step 1: Link density for directed graph

The increase in the number of edges increases the graph density. It can be formulated as below,

$$Edges = size(E_{ij})$$

// Number of formed edges,

$$vertices = size\ (V_{ij})$$

// Number of formed vertices,

$$Dense_{graph} = \frac{2*Edges}{vertices\ (vertices - 1)} \tag{14}$$

Step 2: Average of closeness centrality

The graph can effectively detect the nodes centrality that have capability to spread the information by calculating the closeness of centrality. It can be formulated as below,

$$Closeness_{central}(a) = \frac{size(E_{ij})}{D(a)} \tag{15}$$

where, $D\ (a) = \lim_{a \to 1:size\ (V_{ij},1)} \sum_{b=1}^{size\ (V_{ij},1)} Dist(a,b);$

$$Dist\ (a,b) = \lim_{b \to 1:size\ (V_{ij},1)} \sqrt{(X\left(V_{ij}(a)\right) - X\left(V_{ij}(b)\right))^2}$$

Step 3: Graph Entropy

To characterize the texture of input image, graph entropy is calculated. It can be formulated as below,

$$Entropy = -\sum_{i=1}^{n} P(i) * \log\ (P(i)) \tag{16}$$

Where,

P - Degree Distribution of graph,

$P = \frac{n_k}{n}$

$n_k -$

$number\ of\ k\ connected\ nodes\ to\ the\ particular\ n^{th}\ node.$

n – Number of vertices

Step 4: Average Distribution Weight of the Graph

To detect the similarities or dissimilarities between the vertices connected by the edges, weight is calculated using the below equation (17),

$$Weight_{avg} = mean(W) \tag{17}$$

Where W can be represented as the weight of all edges in a graph.

Step 5: Graph Hilbert Transform (GHT):

To convert the image and to extract the global features, the Hilbert transform method is applied in this work. The Hilbert transform of the graph of a function f(x) can be defined as below,

$$F(t) = \frac{1}{\pi}\int_{-\infty}^{\infty} \frac{f(x)}{t-x} dx \tag{18}$$

The Hilbert transform of a constant is zero. If you compute the Hilbert transform in more than one dimension and one of the dimensions does not vary (is a constant), the transform will be zero (or at least numerically close to zero).

C. Geometric Features:

In a geometric-based approach, the local features that are based on local statistics and locations like bodily features are extracted. It can be implemented in the following ways.

- Convex Area Of Image
- Eccentricity
- Filled Area
- Axis Length
- Orientation

i. Convex Area of Image

The binary image covering the convex area gives the outline of the curved image. The convex area can be denoted as several pixels in a convex image. The convex area can be computed as shown in fig 3

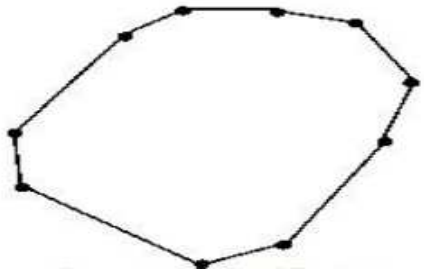

Fig 3 - Convex area of Image

j. The eccentricity of an image:

Eccentricity is the ratio of length pf short or minor axis to the length of the major or long axis of an image. For a linked region of a digital image, it is defined by neighbor graph and calibrated metrics. The number that measures and look of the ellipse by illustrating its flatness is also called as eccentricity. The eccentricity can be calculated by using the given equation,

$$\text{eccentricity} = \frac{\text{lenght of the short axis}}{\text{length of the long axis}}$$

k. Filled Area:

Full Image can be denoted as a binary image of the same size similar to the bounding box of the region. Filled Area is defined as the number of pixels in that particular filled image.

l. Major Axis Length:

The major axis is endpoints of the lengthiest line that is constructed through the image or object. The major axis endpoints are derived by calculating the pixel distance between each grouping of boundary pixels in the object periphery and finding the pair with increased length. Major Axis Length gives the value of the image or object length.

m. Minor Axis Length:

The minor axis endpoint is the longest line that can be constructed through the image or object, whereas remaining perpendicular along with the major axis. Minor Axis Length gives the value of the image or object width.

n. Orientation

The major-axis angle is calculated from the angle between the X-axis of the image and the major axis. It can vary from 0° to 360°. Orientation is defined as the entire direction of the shape of the object in the image.

D. Convolutional Neural Network

The convolutional neural network uses stochastic gradient descent to calculate the minima for the loss function, and it uses the high dimensional dataset to reduce efficiently. Hence it is a greedy technique. It doesn't assure you to find global minima. So the proposed research used an optimization algorithm to minimize the loss function, and it is trained using the back propagation method. The back propagation method initially calculates the dot products of the input signal and its respective weights by activation function to the summation of products. It then transforms the signal to design the complex non-linear functions. The introduced non-linear functions train the design to learn complete random functional mapping. Then back propagation is performed in the system with error terms with updated weight values by Gradient Descent. By applying this, we measure the gradient error, including weight and update in alternate direction of the gradient of the loss function concerning the design parameters.

The extracted features are grouped and passed into the following classifiers

- Convolutional layer
- ReLU layer
- Fully-connected layer
- Soft-max layer

Convolutional layer

- The main aim of the convolution is to derive the meaningful features from the input image
- If an input image, feature detector, and feature map are present, then the filter is deployed to a pixel block by block to the input image by multiplication of matrices.
- The layer applies a filter to develop a feature map that precise the presence of identified features in the input image

ReLU layer

- Rectifier linear unit layer is another frequently used type in the activation function
- The activation function is executed onto the feature maps to upsurge non-linearity in the input images.
- It is applied to the input images that are naturally non-linear by removing all the negative values such as black elements in the image and retain it with only positive values.
- It eliminates the negative value from an image by setting the activation map function to zero

Fully-connected layer

- Fully-connected layer is formed by connecting each neuron in the preceding layer to every neuron in the succeeding layer. It is an ancient multi-layer perceptron
- It is used to classify the features from the output image of preceding layer input image based on the training dataset.

Soft-max layer

- It is the final layer of the proposed network which predicts "n" different classes by calibrating the probability of belonging to every category
- The column feature vector is denoted as x and present in the final layer of the network

$$P(y = j|x, \theta) = \frac{e^{\theta_j^T x}}{\sum_{j=1}^{k} e^{\theta_j^T x}} \qquad (18)$$

θ_j^T is represented as the weight vector, and the target comprises of k classes.

IV. PERFORMANCE ANALYSIS

The experimental analysis is performed by calculating various performance metrics such as accuracy, precision, recall, F1-score, classification accuracy, and recognition rate. It is verified with a different existing method such as FaceNet, CDA, TDL, KCFT, G-FST, and HOD+SVM by using LFW and ORL dataset.

Dataset Description

- Labelled Faces in the Wild (LFW) dataset contains 13,000 images to study the problem of unconfined face recognition, and it is detected by Viola-Jones face detector
- ORL dataset contains the pictures captured from 1992 to 1994 of different subjects under various lighting conditions with several facial expression such as open or closed eyes, smiling and not smiling

A. Recognition Rate

The recognition rate is divined as the summation of correctly identified acquisition image by total number acquisition images by various experimental analysis. Table.1 shows the exploratory analysis of the recognition rate for the proposed and different existing methods is shown.

Tabulation.1 Multi-directional local gradient descriptor: A new feature descriptor for face recognition using different existing methods and the proposed method

Methods	Recognition Rate %
Xing (Ding, Choi, Tao, & Davis, 2015)	74.64–80.82
DML-eig	82.28–87.94
SILD	80.07–86.04
ITML	79.98–85.94
LDML	80.65–86.64
KISSME	83.37–88.92
DLML	85.35–91.15
PFFT features	97.07
MLGD (Kagawade & Angadi, 2019)	97.25
Proposed	99.12

B. Classification Accuracy

Classification accuracy is defined as the ratio of total quantity of accurate prediction images to the total quantity of input images by using various experimental analysis. Table .2 shows the result of classification accuracy by using existing and proposed methods. It is proved that the proposed method gives give the value of accuracy

Tabulation – 2. Ensemble of texture and shape descriptors by existing and proposed method

References	Classification Accuracy (%)
Juefei-Xu et al. (Mowbray & Nixon, 2003)	87.55
Ensemble Texture Descriptors (VenkateswarLal, Nitta, & Prasad, 2019)	91.8
DCSD(VenkateswarLal et al., 2019)	92.5
Proposed	99.12

C. Accuracy

Accuracy is calculated to evaluate the performance metrics of our proposed system. It is shown in Fig 2 and Table 3 that the proposed method gives high efficiency when compared with another existing method. From the fig 2 and 3, it is shown that the value of accuracy is high in the proposed method using a real time dataset from the image fig 6 and compared to other existing methods such as Face Net, CDA, TDL, KCFT, G-FST, and HOD+SVM by using LFW and ORL dataset.

Tabulation – 3 Enhanced Human Face Recognition Using LBPH, Descriptor, Multi-KNN, and Back-Propagation, Neural Network and Proposed method

Reference	Method	% Accuracy

(Dadi, Pillutla, & Makkena, 2018)	PCA+BPNN	88
(L. Li, Ge, Tong, & Zhang, 2018)	LDA	89.5
(Pan, Wang, & Cheng, 2016)	Gabor + NMF	95
(Ding & Tao, 2015)	DCT	91.5
(Zhang & Peng, 2017)	FKNN	87
(Zeng et al., 2018)	WT+PCA	95
(Min, Xu, & Cui, 2019)	CASNN,FFNN	86.5
(Min et al., 2019)	PCA + DCT + Corr +PIFS	86.8
(Min et al., 2019)	LBPH, Multi-KNN & BPN	98
Proposed	LPQ, DG, CNN	98.023

D. Precision

Precision is a significant performance metric calculated to find the positive predicted values. It is the fraction of related instances from the extracted cases. From the fig 2 and 3, it is shown that the value of precision is high in the proposed method using a real-time dataset from the image fig 6 and compared to other existing methods such as Face Net, CDA, TDL, KCFT, G-FST, and HOD+SVM by using LFW and ORL dataset.

E. Recall

The recall is termed as sensitivity that is the ratio of total quantity of related instances that are truly retrieved. From the fig 2 and 3, it is shown that the value of recall is high in the proposed method using real-time dataset from the image fig 6 and compared to other existing methods such as Face Net, CDA, TDL, KCFT, G-FST and HOD+SVM by using images from the fig 4 and 5 of ORL and LFW dataset

F. F1-Score

It is one of the critical performance metrics to test the accuracy of the proposed method. It is shortly defined as the weighted harmonic mean of tested values of recall and precision. From the fig 2 and 3, it is shown that the value of recall is high in the proposed method by using input real-time dataset images from the fig 6. It is compared to other existing methods such as Face Net, CDA, TDL, KCFT, G-FST, and HOD+SVM by using the pictures from the fig 4 and 5 of ORL and LFW dataset.

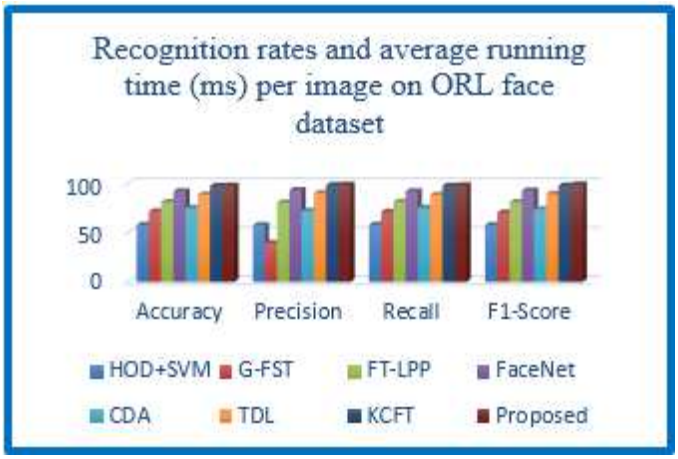

Fig 2 – Comparison of Performance metrics using the different existing method and proposed method in ORL dataset

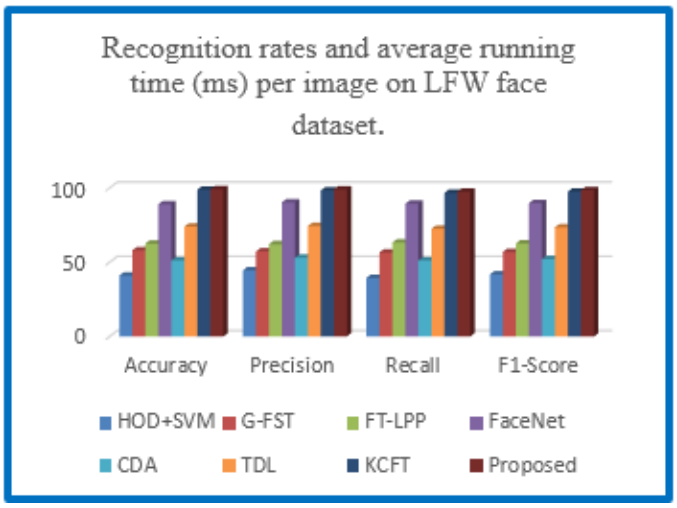

Fig 3 – Comparison of Performance metrics using the different existing method and proposed method in LFW dataset

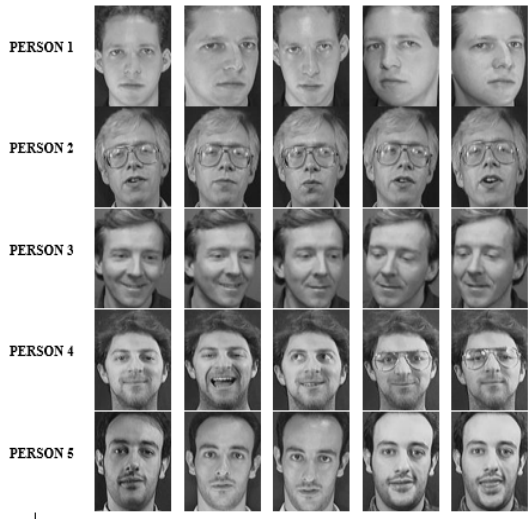

Fig – 4 ORL dataset of various person

Fig – 5 LFW dataset of various person

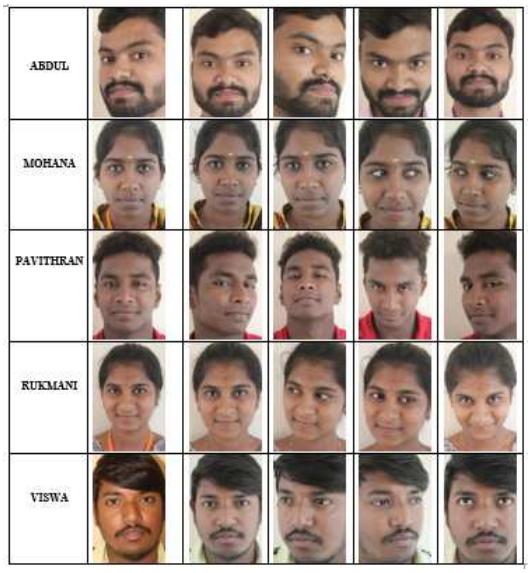

Fig – 6 Real-time datasets of various person

V. CONCLUSION

In this research, we proposed the novel technique that gives a high accuracy rate of face recognition by using Local Phase Quantization (LPQ), Geometric-based features and direction graph-based feature extraction methods, and Convolutional Neural Network. The novel based convolutional neural network is used for effective person recognition that is implemented for criminal identification and to evaluate the casual visit of a person to the mall. Various experimental and performance analyses such as classification accuracy, recognition rate, recall, precision, and F1-score performance value of the proposed technique outperforms other existing methods by high efficiency and recognition value ensuring its supremacy over existing methods.

DECLARATION

I Am P. Karuppanan Hereby State That The Manuscript Title Entitled "**A Novel Feature Extraction Based Person Recognition Using Local Phase Quantization And Geometric Features**" Submitted To The **"Wireless Personal Communication Systems"**, I Confirm That This Work Is Original And Has Not Been Published Elsewhere, Nor Is It Currently Under Consideration For Publication Elsewhere. And I Am Assistant Professor In the Department of Computer Science and Engineering, Pandian Saraswathi Yadav Engineering College, Sivaganga.

I'm the corresponding author of our paper, my contribution work on this paper is to Writing, developing, and reviewing the content of the manuscript. And my co-author K. Dhanalakshmi works were to cite the figure, table and references. Equally I have done 50% and my Co-Author has done 50% of the work. We are the entire contributors of our paper. And there is no any other third party people are not involved in this paper.

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Figures

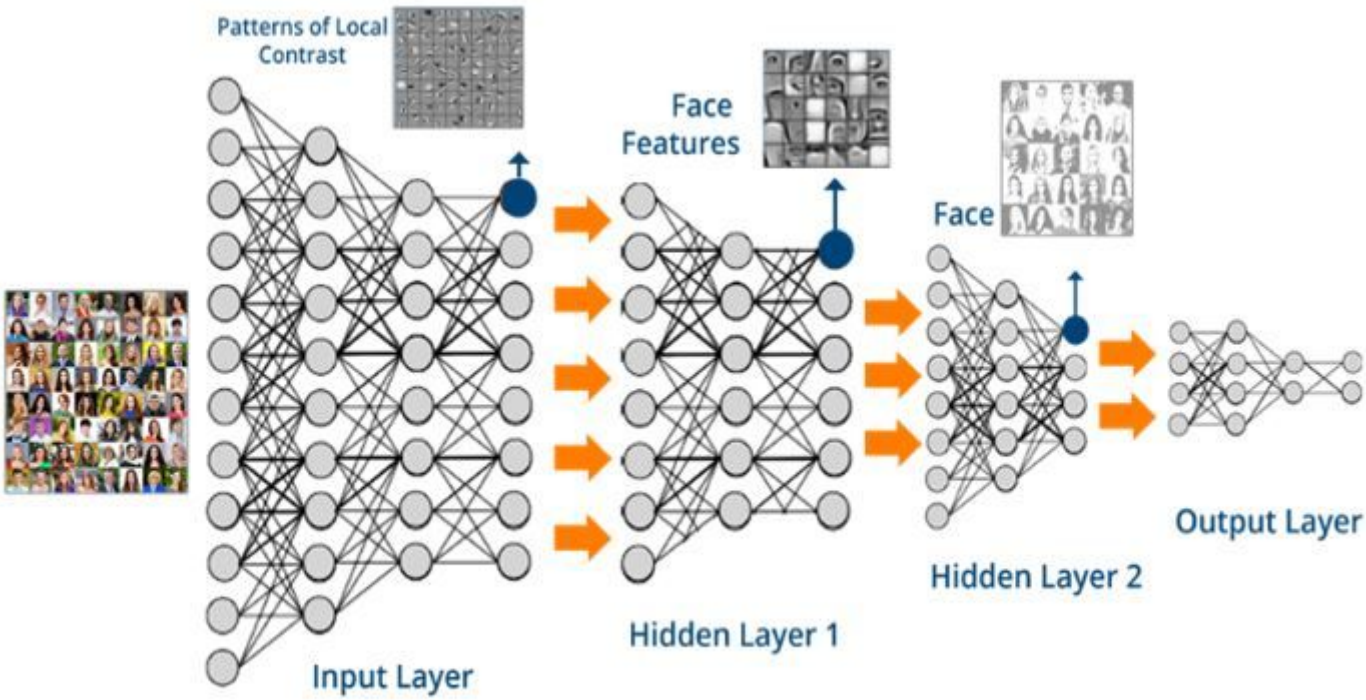

Figure 1

Schematic diagram of Convolutional Neural Network

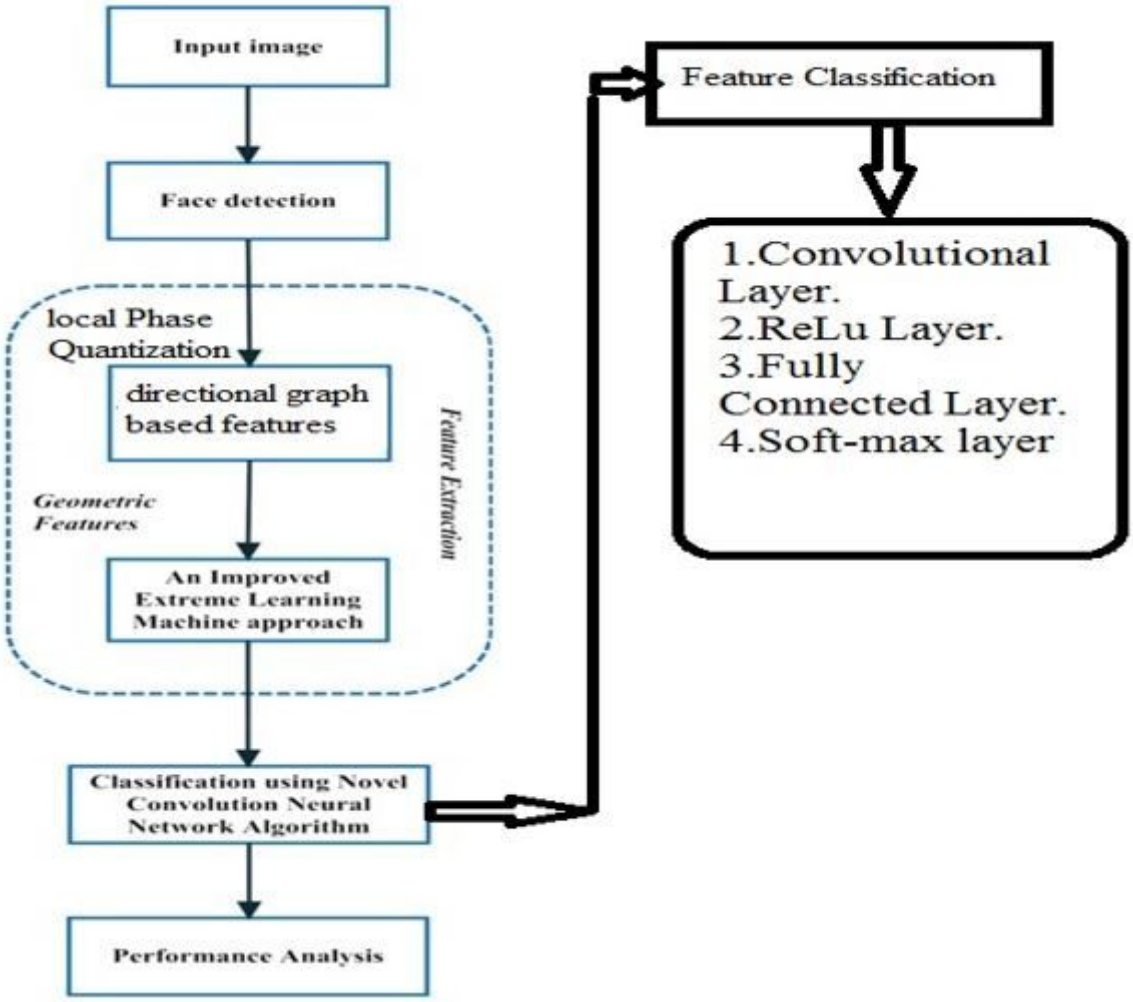

Figure 2

Architecture of the proposed system

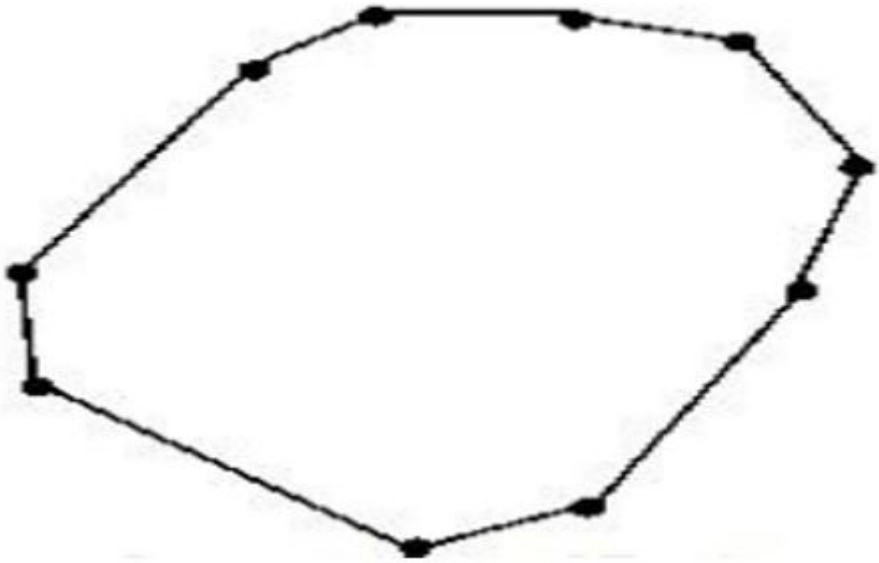

Figure 3

Convex area of Image

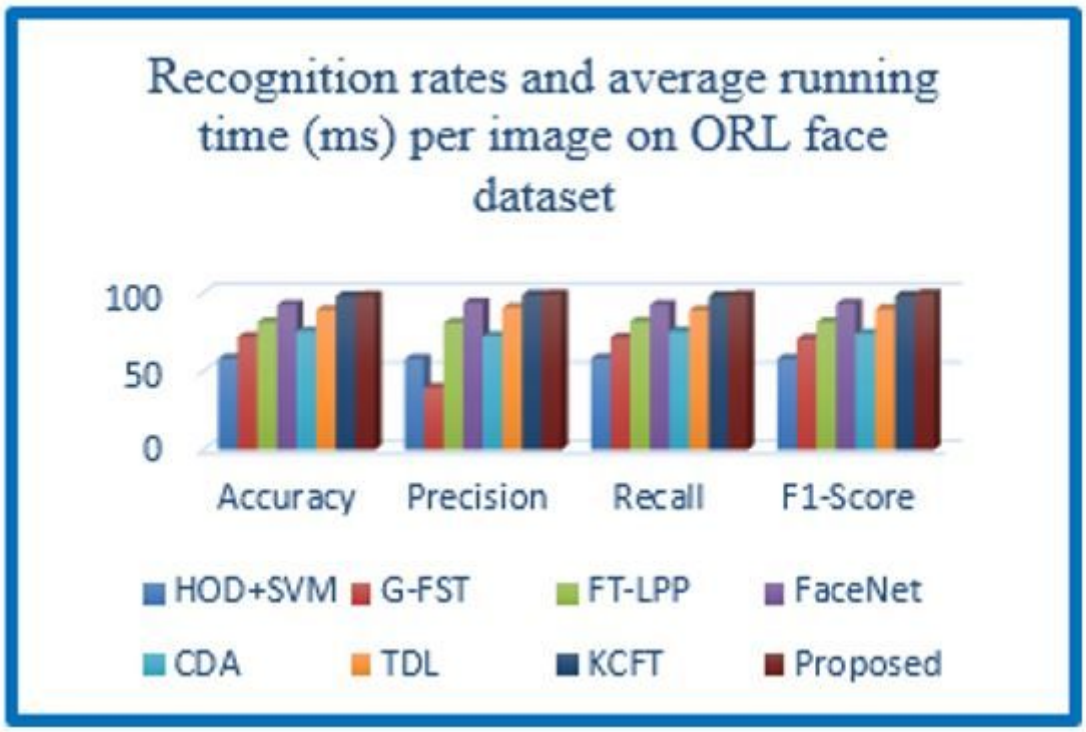

Figure 4

Comparison of Performance metrics using the different existing method and proposed method in ORL dataset

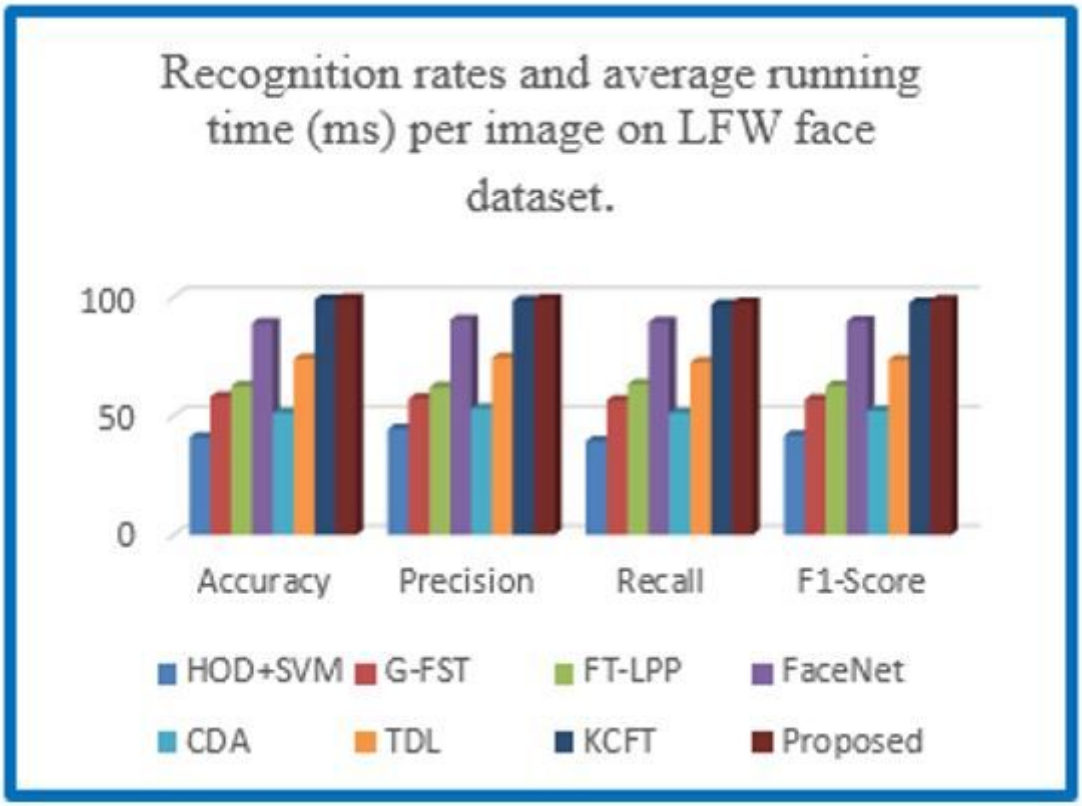

Figure 5

Comparison of Performance metrics using the different existing method and proposed method in LFW dataset

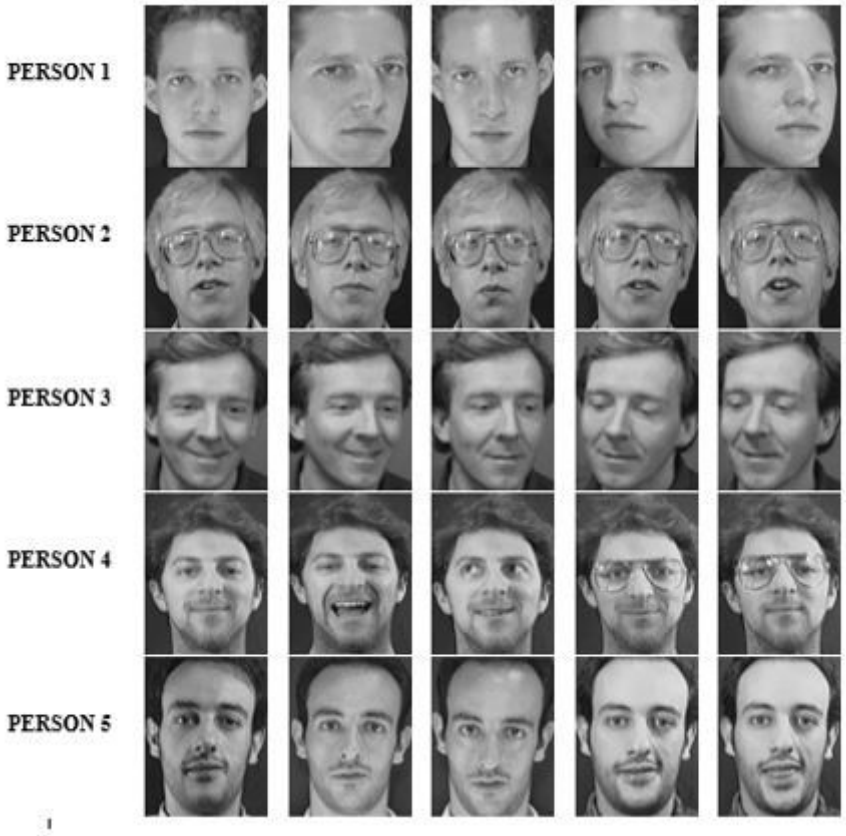

Figure 6

ORL dataset of various person

Figure 7

LFW dataset of various person

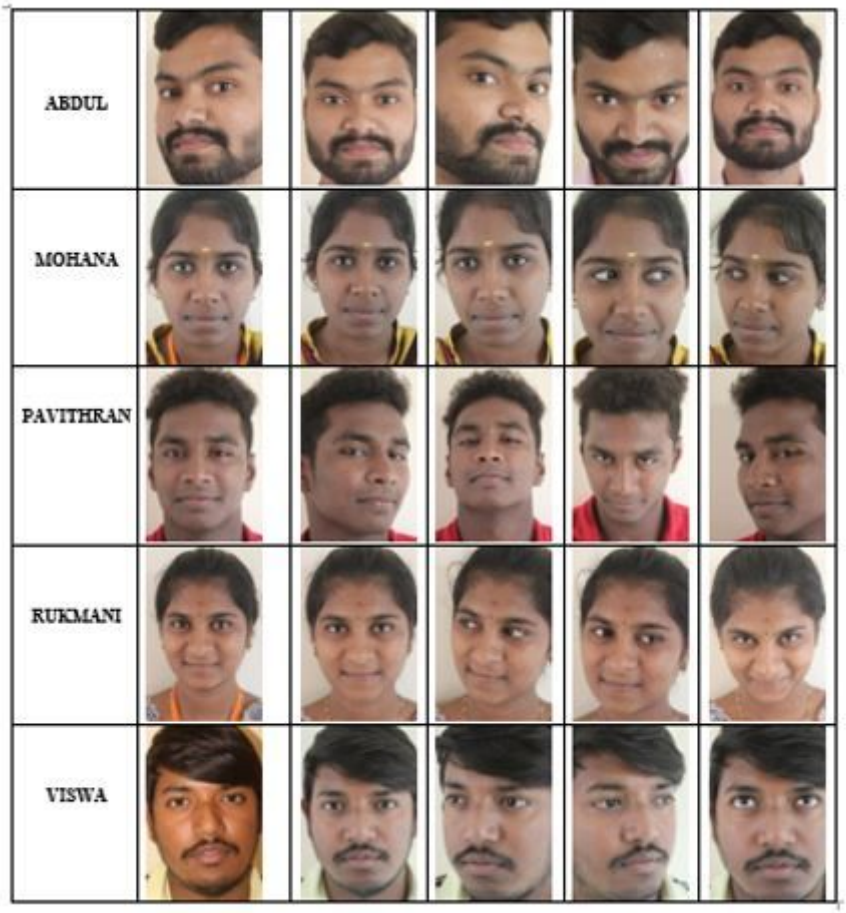

Figure 8

Real-time datasets of various person