T.C.
ISTANBUL AYDIN UNIVERSITY
INSTITUTE OF GRADUATE STUDIES

INTELLIGENT FACE RECOGNITION SYSTEMS

MASTER'S THESIS

Ömer ŞAHİN

Department of Electrical and Electronics Engineering
Electrical and Electronics Engineering Program

July 2021

T.C.
ISTANBUL AYDIN UNIVERSITY
INSTITUTE OF GRADUATE STUDIES

INTELLIGENT FACE RECOGNITION SYSTEMS

MASTER’S THESIS

Ömer ŞAHİN

(Y1813.300020)

Department of Electrical and Electronics Engineering
Electrical and Electronics Engineering Program

Thesis Advisor: Assist. Prof. Dr. Necip Gökhan KASAPOĞLU

July 2021

ONAY FORMU

DECLARATION

I hereby declare with the respect that the study "Intelligent Face Recognition Systems", which I submitted as a Master thesis, is written without any assistance in violation of scientific ethics and traditions in all the processes from the project phase to the conclusion of the thesis and that the works I have benefited are from those shown in the Bibliography. (24/09/2021)

Ömer ŞAHİN

FOREWORD

I would like to express my full appreciation and gratitude to my thesis advisor, Assist. Prof. Dr. Gökhan Kasapoğlu for his guidance, support and for pushing me forward to work hard on my thesis.

And to my family and friends specially my mother who shows her caring, patience and understanding. Also, to my manager and co-workers who stand by my side and make it easy for me to study and complete my thesis.

July 2021 Ömer ŞAHİN

INTELLIGENT FACE RECOGNITION SYSTEMS

ABSTRACT

Face recognition methods and algorithms have been improved during the last years. A lot of research and studies have been done to establish high accuracy and fast recognition rate in face recognition systems. Although various results were estimated using different techniques to reach best accuracy and performance. This leads us to continue the wheel of improvements to conduct more studies about face recognition techniques.

In this thesis we make comparison with the most known traditional technique of face recognition EigenFace using principal component analysis (PCA) algorithm, Linear discriminant analysis (LDA) Fisher face approach and Local Binary Patterns (LBP). An enhanced comparison with some of the most recent advanced techniques related to deep learning and neural networks. Results shows that advanced techniques that depend on deep learning algorithms outperform traditional techniques in terms of accuracy and computational time. On the other hand, among the traditional tested techniques, we notice that LBP gives the best accuracy with 96% and 89% when compared using the CALTECH and FEI datasets respectively.

Keywords: Face Recognition, PCA, EigenFace, LDA, LBP.

AKILLI YÜZ TANIMA SISTEMLERI

ÖZET

Yüz tanıma yöntemleri ve algoritmaları son yıllarda sıklıkla kullanılmaktadır. Yüz tanıma sistemlerinde yüksek doğruluk oranı ve hızlı tanıma sağlamak için birçok araştırma ve çalışma yürütülmüştür. En iyi doğruluk ve performansa ulaşmak için farklı teknikler kullanılarak çeşitli sonuçlar elde edilmesine rağmen, başarımı ve performansı veriye bağlı iyileştirmek için daha fazla çalışma yürütmek gerekmektedir.

Bu tezde, temel bileşen analizi (PCA) algoritması, doğrusal ayırıcılık analizi (LDA) Fisher yüz yaklaşımı ve yerel ikili modeller (LBP) kullanarak en bilinen geleneksel yüz tanıma tekniği olan EigenFace ile karşılaştırmalar yapılmıştır. Bu temel karşılaştırmanın yanında derin öğrenme ve yapay sinir ağları gibi göreceli olarak yeni tekniklerle de karşılaştırma yapılmıştır. Sonuçlar, derin öğrenme algoritmalarına dayanan gelişmiş tekniklerin, doğruluk ve hesaplama süresi açısından geleneksel tekniklerden daha iyi performans gösterdiğini göstermektedir. Öte yandan, geleneksel test edilmiş teknikler arasında, LBP' nin sırasıyla CALTECH ve FEI veri setleri kullanılarak karşılaştırıldığında %96 ve %89 ile en iyi doğruluğu sağladığı gösterilmiştir.

Anahtar kelimeler:. Yüz Tanıma, PCA, EigenFace, LDA, LBP.

TABLE OF CONTENT

ABBREVIATIONS

NN	Neural Network
CNN	Convolution Neural Network
PCA	Principal Component Analysis
SVM	Support Vector machine
KNN	K-Nearest Neighbor
LDA	Linear Discriminant Analysis
LBP	Local Binary Pattern
RR	Recognition Rate

LIST OF TABLES

LIST OF FIGURES

I. INTRODUCTION

Machine learning opens the door for artificial intelligence to help researchers developing wide range of industries. This was done by understanding and learning each type of data to make the outcome predictable with high accuracy algorithms.

These days the demand on AI technologies and machine learning increased significantly, one of the machine learning topics that has been focused on is Facial Recognition, it is branch of biometric identification technology and its used in various frameworks such as business, economy, culture, politics, military. e.g. Police use facial recognition to recognize wanted criminals, or surveillance Purposes, Airports and Banks use it for Person Verification, film and graphics industries to preform particular manipulation with characters facial expressions.

Also, specially through the Covid-19 crisis and with the new rules followed for social distancing, business companies start replacing their traditional Attendance Systems (fingerprint, RFID cards) with facial Recognition Attendance System to reduce infection and limit touching same objects by a lot of people.

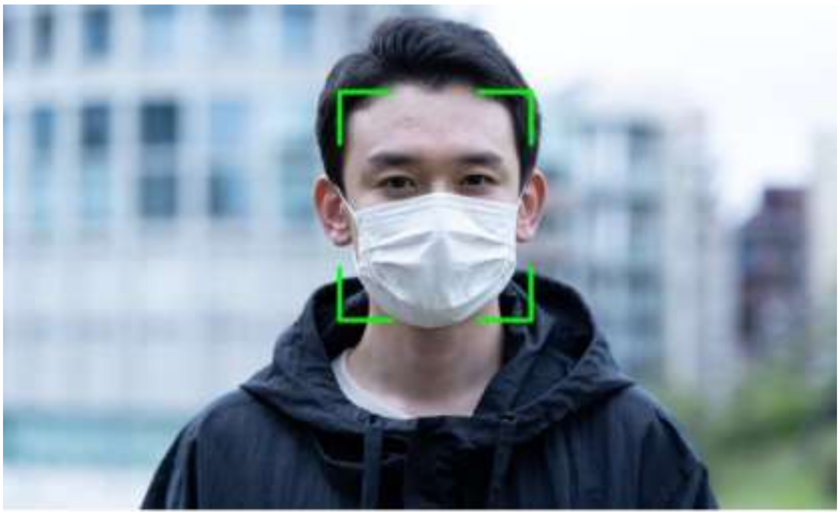


Figure 1 Masked Face Recognition**.**

Therefore, there is no need to check that you have your access ID card or your location device if the company uses a Global positioning system (GPS) however it is a potential security issue because the ID card or the (GPS) device can be held with anyone else. Therefore, using systems that depends on human biometrics without the need with external devices, is more reliable, flexible, and safe specially if it's based on computer vision and machine learning.

Face Recognition technical Process comes as Follows:

Figure 2 Face Recognition Process.

First, the system needs to check the face in the image and coordinates the face area inside the image. Then, detect and locate the facial feature points of face organs eyes, eyebrows, nose, and mouth. Based on these features a detail of this face should be obtained by specific algorithms. After that, a comparison will be made with the already existed details of faces in our database to establish face recognition.

A. Thesis Object

Face Recognition witnessed a lot of development and new approaches. In this thesis we are going to pass through some traditional techniques of face recognition, Principal Component Analysis (PCA) algorithms (EigenFace), linear discriminant analysis (Fisherface) and local binary pattern. Also, to check some recent advanced techniques using neural networks. Main objective of this thesis is to implement a face recognition system using these different approaches to compare performances, quality and accuracy. each approach should detect faces in live acquired images and detected faces should be recognized.

B. Thesis Outlines

This research has 6 chapters, in the first chapter we made a brief introduction on our topic face recognition.

- The second chapter contains the literature review of writing studies on face recognition. It endeavored to be focused on the most significant methodologies and results.
- In the third chapter we introduced the methods that we want to focus on and implement to make the comparison.
- In the Forth chapter, we observed some of the most recent techniques related to neural networks which has a great impact nowadays.
- In the fifth chapter we implemented and tested the mentioned methods with showing comparison in accuracy and some advantages and disadvantages.
- In the last chapter we concluded a summary for the work has been done and share some future work to be done.

II. LITERATURE REVIEW

In this chapter we will take a closer look on some research has been done in the field of face detection and recognition.

A. Detection Review

Face detection is the initial part of face recognition framework. Yield of the detection can be the coordination of face district facial highlights (eyes, eyebrow, mouth, nose etc.). Most of the calculations are mix of techniques for distinguishing countenances to expand the exactness. Predominantly, recognition can be ordered into two gatherings as Information Based Strategies and Picture Based Techniques.

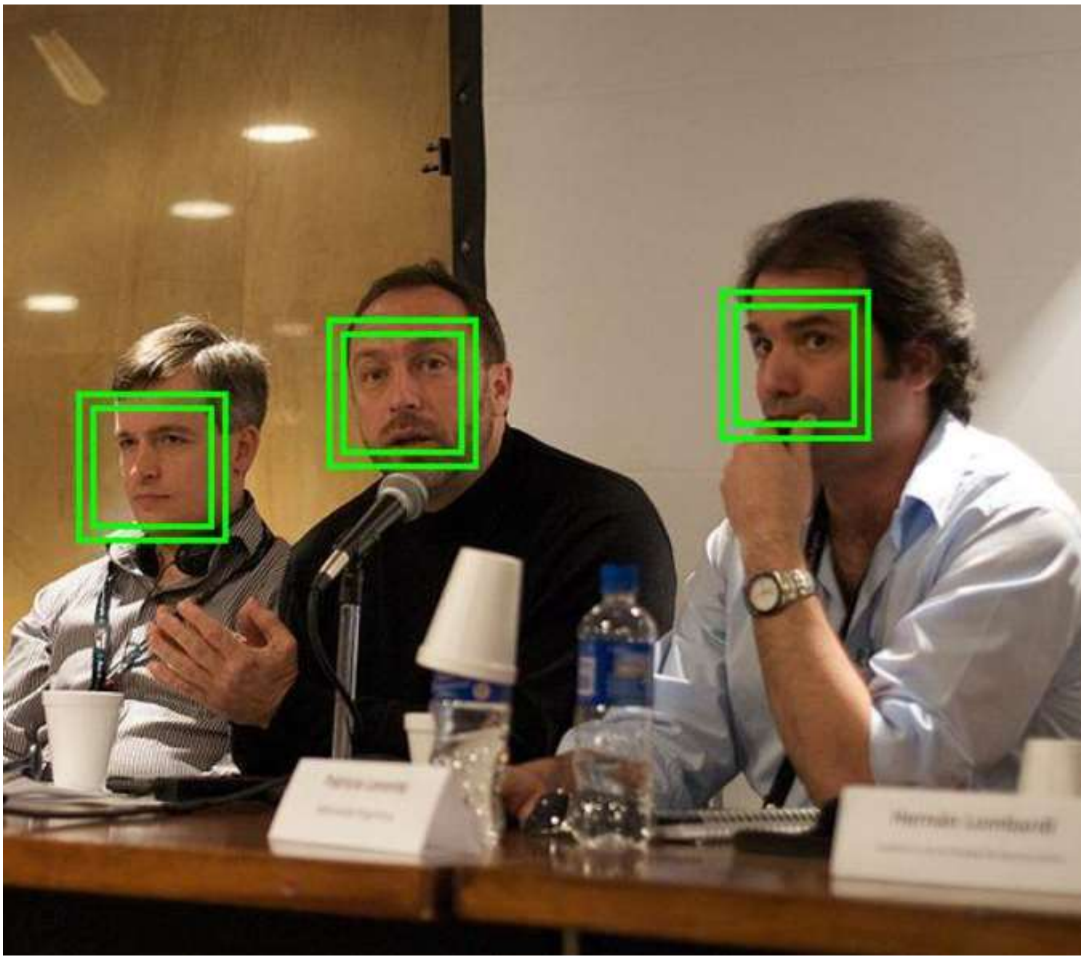


Figure 3 Detection of Multiple faces.

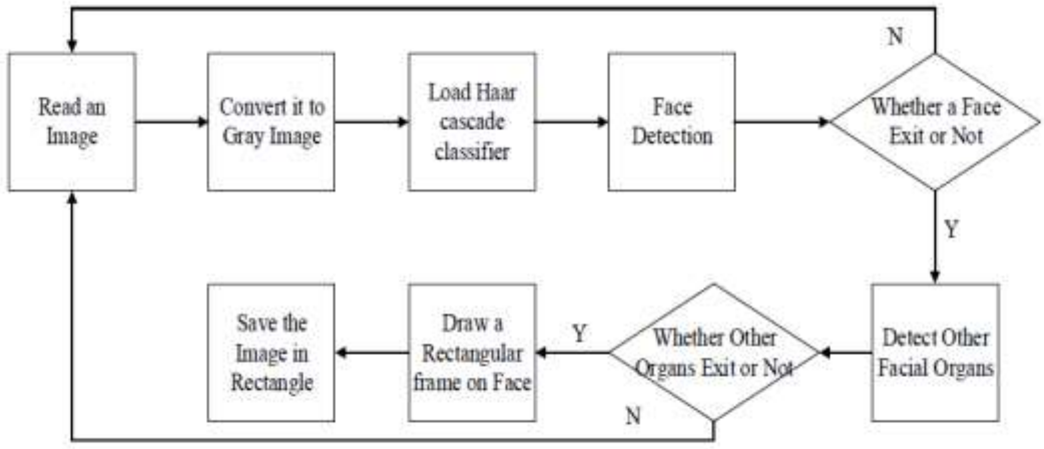


Figure 4 Face Detection workflow**.**

Information Based strategies use data about Face features, Skin color or comparing templates. Face features are utilized to discover eyes, mouth, nose, or other face features to catch the human faces. Skin color is not the same as other colors and its exceptional, and its qualities don't change concerning changes in posture and obstruction. Skin color is demonstrated in each shading spaces like RGB (Red-Green-Blue), YUV (Luminance-Blue Luminance Distinction Red Luminance Contrast), and in measurable models. Face has an exceptional pattern to separate from different items, subsequently a layout can be created to check and identify faces.

Detecting faces and face features by the extraction of skin district with YCbCr color space and edges were identified likewise in the skin locale. Another methodology removes skin like district with Standardized RGB colored space and face is checked by comparing templates. To discover eyes, eyebrows and mouth, coloring snakes are applied to checked face pictures. Another application fragments skin like districts with measurable model. Measurable model is produced using skin coloring esteems in Cb and Cr direct in YCbCr coloring space. Then, at that point, face applicants are picked concerning rectangular proportion of sectioned locale. At last, the applicants are confirmed with eye and mouth map.

Skin color is perhaps the most clear features of people faces. Skin color can be displayed with defined or non-defined strategies, additionally can be distinguished as far as limit area, curved demonstrating, factual displaying like Gaussian Demonstrating or Neural network. Skin tone is depicted in all shading spaces like

RGB, HSV, and YCbCr. RGB is easily affected by to light intensity however YCbCr and HSV are not delicate to light intensity, on account of these color spaces have separate force and coloring channel.

Another methodology prior to find faces is to do white balance adjustment. The coloring esteem is significant for division. Therefore, having the picture color could give false one. To disregard this, white balance adjustment must be made mainly from that point onward, skin coloring locales are sectioned utilizing curved model in YCbCr. After skin districts are discovered, they joined with edged pictures to grayscale picture. At long last, the consolidated districts are confirmed to be a face by checking bounding box proportion and the region in that bounding box. Face Patterns is another important data about face detection. Face-template could be done for the sectioned area. Checking procedure is applied with little size window.

This methodology checks everywhere on the first picture, and afterward diminishes the picture size with some emphasis reasonable to re-filtering. Diminishing the size is imperative to find the enormous or medium size faces. Nonetheless, this requires more time of calculation to find faces. Face templates in sectioned district needs less calculation time than scanning the reason is it is just coordinating of sectioned part templates or patterns, which are not picture-like however made of certain boundaries like size, shape, shading, and area section. Skin like areas are fragmented concerning YCbCr coloring space. Then, at that point, eye and eye pair unique patterns are applied to the sectioned locale. First pattern finds the district of eyes and second pattern find each eye and its direction. after that, at that point structure template is applied to confirm the face detected section.

Image Based strategies does training or learning to make correlation among faces and other objects. For these sort of techniques, huge number of pictures of faces or objects brought for training to enhance the exactness of the system. EigenFace, AdaBoost, NN and SVM are the most techniques usually utilized in face detection. Faces and objects pictures are depicted as far as wavelet include in AdaBoost strategy. PCA is utilized to create the features vector of face and objects pictures in EigenFace technique. Additionally, PCA is utilized to reduce the dimension of the given data vector. Kernel functions are made to portray face and objects pictures in support vector machines. Faces and objects’ pictures can additionally be detected through artificial neural networks. AdaBoost develops solid classifier from frail classifiers.

Identification is reached through cascade classifier. This method can deal with faces; left and right+45-degree rotation.

In matching templates to detect faces was applied. The matrix of the image is straightforwardly given to PCA rather than vector. That diminishes calculation time for finding the covariance matrix. when PCA is processed, minimum distance classifier is utilized to arrange the PCA information for both faces or object situations. Another strategy utilizes PCA with neural networks. PCA is processed to the offered picture to detect faces. At that point, face pictures are grouped with NN to take out any object’s pictures other than faces. In other study, likewise, PCA and AdaBoost applications were done with window scanning strategy. After PCA is processed, the given feature vector is utilized as contribution of AdaBoost strategy. Solid classifier is produced from PCA feature vectors to be used in AdaBoost technique.

B. Recognition Review

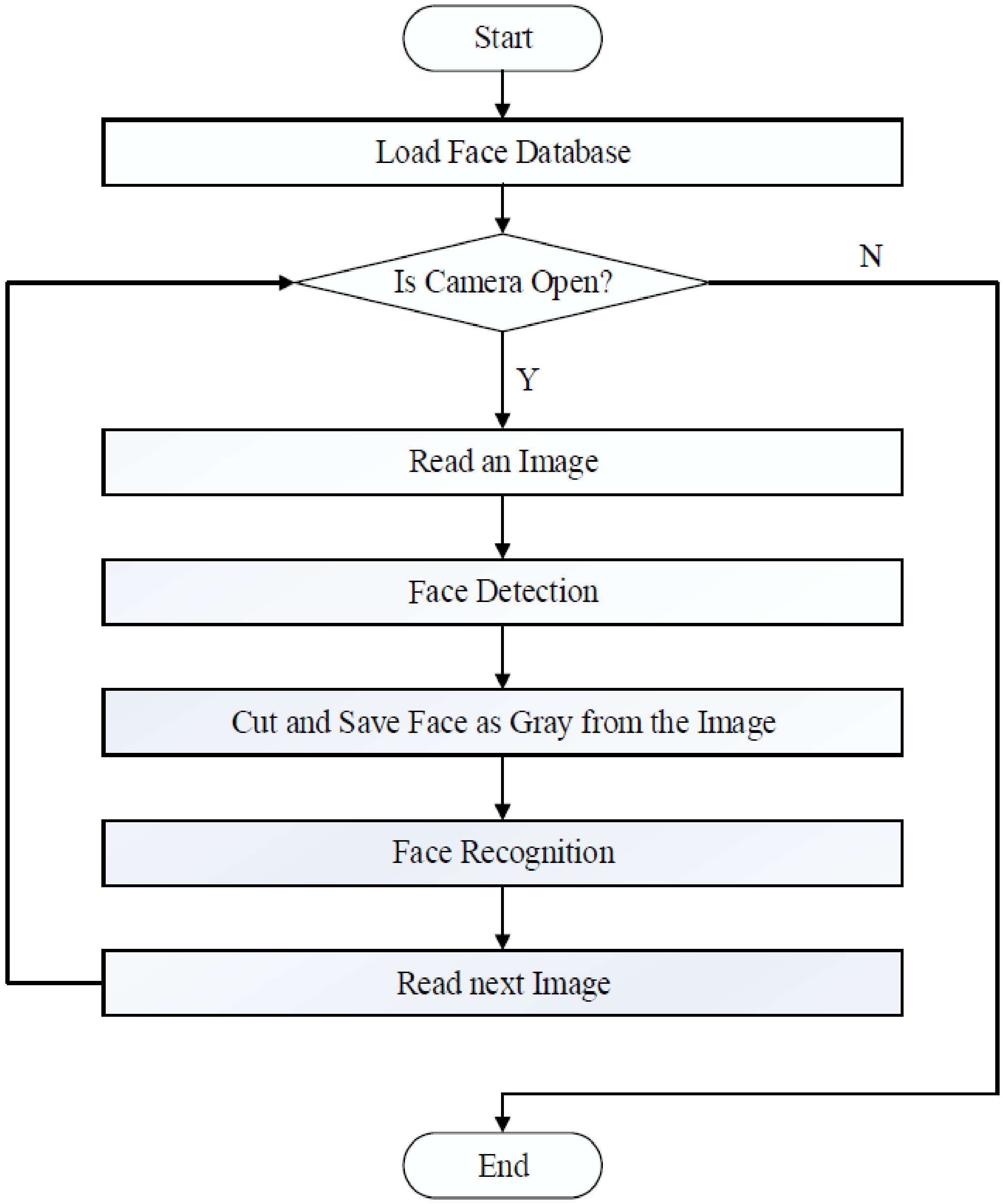


Figure 5 Basic Workflow of Face Recognition.

A technique was recommended called MBS Minimum Bending Synthesizing depends on the design of a front face by contemplating and diminishing the amount of deformation of twisting being utilized and by choosing the grey saturation in consensus same as a front facing view from numerous non-front facing input pictures. This technique tried to reproduce the differentiation that establishes a characteristic human face, also, it would help improving exemplary techniques for precision. Both PCA and LDA were implemented to solve issues of posture. The examinations on the CMU PIE and FERET data sets with this technique accomplished a high recognition rate.

Here is the Joint Dynamic Sparse Representation technique was proposed that uses classification. This technique chips away at multi-face acknowledgment and accomplishes the sturdiness to sparse representation based on classification. In addition, through the assorted perspectives, it gave benefits by utilizing correlation and tests on the data sets (CMU Multi-PIE). Right off the bat, the proportion of acknowledgment under different angles was in the range of 50%-85%. Also, Identification with different feature dimension was more than 82%.

Also, a recommended technique that relied upon complex wavelet moments. This recommended technique utilizes together nonexistent and genuine (real & Img.) elements of moments, along these lines reduplicate the amount features according to the significant features of wavelet minutes. Turn invariance was obtained after amending the real and imaginary components of wavelets. This technique acquired a recognition accuracy of 90.0% on the FERET information dataset and 98.9% on the JAFFE data set.

Another proposed technique for face identification that relied upon PCA picture remaking and LDA. This technique utilized the internal class covariance matrix to separate features. For each individual, it finds the matrix of covariance and the eigenvectors after that, to get the recreated pictures. Then, features were utilized for learning and testing support vector machines to get the required face Identification. The ORL face data set was utilized for tests. This strategy accomplished an accuracy around 96% when utilizing a minimum distance classifier, though utilizing SVM acquired an accuracy around 97%.

Here also a technique is called the Multiple Kernel Local Fisher Discriminant Analysis. The technique considers several features according to many kernel bases. The test made on chosen data sets was as per the following, the exhibition on the ORL data set was in the range of (95.5%-98%), the Yale data set was in the range of (74%-91%) and on the PIE data set was in the range of (71%-95%).

Another technique is to conquer the shortcoming of a pictures quality under various lighting conditions by utilizing Stage Setting relying upon the Fourier transformation phase. In this research was declared that the relevant phase creates a much special code filtration response also a much effective features than the local phase quantization. The test outcome got by the use of the strategy to the chosen data sets were as per the following: CMU PIE was around 98.6%, and YALE-B was around 75.7%.

A research proposed a sparse representation of Discriminative Low rank recovery strategy for face identification, that extended the sparse representation method by combining the low-rank construction of information identification. This technique was ready to recover a right way reference by advancing a discriminative ability from harmed training images for sparse identification when simultaneously finding a low rank projected matrix to enhance the new sets. It was stated that this strategy was solid to face expressions, lighting changes, and obstacles by utilizing a low rank projecting grid and discriminative recreation error to classification of testing images. The trials in Yale B data set shows that this strategy got an accuracy rate around 86% while the data sets of AR has gotten a rate around 76%-94%.

A method was proposed to deal with light changes for images of faces. This methodology depends on these stages: first one is to utilize the versatile homomorphic filter to decrease the lighting in the image to a certain point. Next the utilization of the worked-on LFD strategy to extract face features. After that utilized a total enhanced local direction pattern, that utilizes the sizes and directional of the edge reactions to give the correct lighting change. Therefore, that enhanced the recognition rate of the process.

Here also a recommended one which is a posture variation face Identification strategy that relied upon multi headed self-attention and the component analysis PCA features approach. Hypothetically, the recommended technique was investigated and assessed tentatively by utilizing four face information datasets. It examined the chance to affect the posture variation, the lighting differences and the noise filtering of the given features.

Recognition could be accomplished with 2D or 3D picture information, the two of them obtain benefits and hindrances. 2D picture information can be acquired effectively and more affordable than 3D. But again, 2D pictures are delicate to light differences yet 3D pictures don't. In 3D pictures, surface of the face could be shaped smoothly, yet 2D pictures doesn't contain the profundity information. Additionally, face Identification calculations are processed using database of faces. This database is made by unique face pictures, therefore the face Identification should manage this issue. Face recognition is considered recognizing a pattern challenge, although training got to be utilized to establish correlation among faces.

III. Geometric approach & PCA

Historically, at the first stage of face recognition it was mainly established by studying the features of face geometric structure. This algorithm has been improved with the development of science and technology. The basis of manually locating the feature points, the factors such as ratio distance of facial feature points were used as features for face recognition. How these systems work they reach a vector, describing the face, that contains a combination of a detected face features and their geometric discriminatory and the distance measurements between these features. From this vector a comparison was made with other existed vector images in the database to preform recognition, but because it carries out mathematical linear simplification faces cannot be described with a high precision. But for some situations, e.g., changing of expressions and shape differences because of aging for instance could affect robustness and tends to give low accuracy.

A. Face Recognition using PCA

Principal Component Analysis is used to extract features and to reduce dimension. Although it is probably the most popular multivariate statistical technique, and it is used by almost all scientific disciplines. PCA is used in image processing, data science, signal processing and other predictive analysis studies. The main target of PCA is to extract the important and interesting main data features and ignore other data for dimension reduction, this way becomes easier to visualize data and it helps in classification.

As far as PCA was concerned, there was motivation to perform facial recognition that is why EigenFace method was proposed which is the set of eigenvectors represents the feature vector of human face calculated from the covariance matrix of the trained data.

There are different kind of distance measurements to use in PCA as a similarity metric like Euclidean distance and other metrices. The classification can be done by measuring similarity between the test image and the trained faces. Following these PCA calculation steps:

First, the preprocess step is reading data images, faces with colored format will be converted into Grayscale images. Next we find the mean matrix of the images to use it in our calculations. Then we find covariance matrix. After that, from covariance matrix we get eigen values and eigen vectors. Now the image I with dimensions (N×N) will be converted into a vector array of dimension N^2.

The main object of principal component analyses is to find the vectors that best describe the distribution of face images in the entire image space. Let (X1, X2, X3,……, Xm) be a training set of the database of face images, then we find the mean face matrix of this set is:

$$\varphi = \frac{1}{M}\sum_{i=1}^{i=m} Xi$$

Equation 1

Where: φ is the mean vector of images, M: the no. of images, Xi: image vector

Φi is the difference between the image Xi and the mean image φ

$$\Phi i = \mathrm{X}i - \varphi \, , i = 1,2,3..M$$

Equation 2

Then A determined by the difference vectors

$$\mathrm{A} = [\Phi_1, \Phi_2, \Phi_3, \Phi_4, ..\Phi_M]$$

Equation 3

The matrix obtained (A) is then multiplied by the transpose of itself

Hence, C the covariance matrix is evaluated:

$$\mathrm{C} = A^T A$$

Equation 4

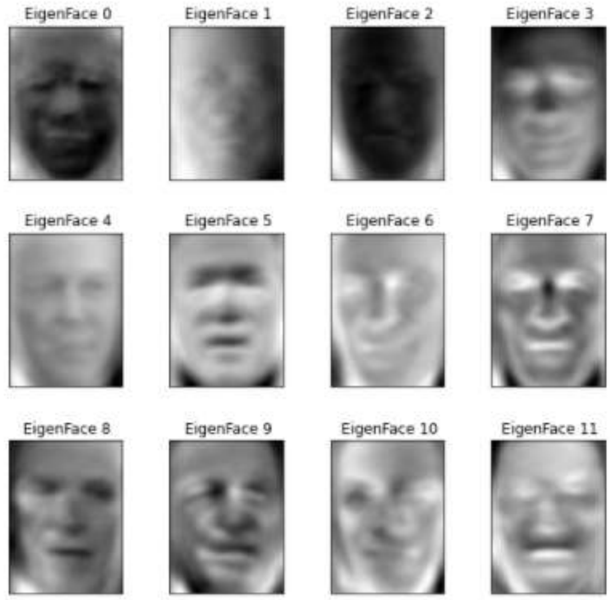


Figure 6 Eigen Faces obtained.

From the covariance matrix eigen values and eigen vectors were obtained, eigen vectors has the same dimensionality as the source images. These Eigen vectors obtained are called the eigen faces. Discriminative features of face would be retained. After finding eigen vectors and eigenvalues from the training images we preserve the images that is related to the highest eigen values.

Those pictures characterize the face space. when new images of faces introduced, the eigenfaces could be remeasured or upgraded. Compute the relating distribution in the weight space for every single face, by projecting their face pictures into the face-space.

Images in the database are saved as groups of weights that reflects contribution each eigen face has to the image. when a face presents its weights will be projected to the group of eigenfaces in the database and then to be identified with the minimum differences.

In Testing we used LFW (Labeled Faces in the Wild) database, we obtain:

Table 1 Accuracy and Prediction Results.

	PRECISION	RECALL	F1-SCORE
PERSON1	78%	54%	64%
PERSON2	83%	87%	85%
PERSON3	89%	63%	74%
PERSON4	83%	98%	90%
PERSON5	95%	80%	87%
PERSON6	100%	53%	70%
PERSON7	97%	81%	88%
ACCURACY	86%		

The rate of positive class predictions among the positive class this refers to be precision (means percentage of results which are relevant). Recall gives the rate of positive predictions among all positive examples in database (percentage of total relevant results correctly classified). F-Measure gives a balanced score of the concerns of precision and recall in a specific rate. A higher rate of F1-score is a better result would be. A classification with high recall means lower false negative and a high precision means less false positive.

B. Face Recognition using LDA

Linear discriminant analysis a strategy utilized in measurements and different fields, to track down a straight mix of features that describes or isolates many classes of faces or objects. The subsequent mix might be utilized as a linear classifier, or to reduce the dimension of images to be classified after that, similarly to the principal component analysis both of them are considered linear collection that best clarify the data, but LDA directly try to demonstrate the difference among the classes of information. PCA, conversely, does not consider any distinction in classes.

The LDA method utilizes the PCA subspace projection as an initial phase in handling the picture information. Consequently, the Fisher Direct Discriminants are characterized in the d dimensional sub space characterized by the primary d head parts. Fisher's strategy characterizes main vectors according to how many classes we have.

Those main vectors could be considered as rows in the matrix, and the discriminants are characterized as those main vectors that amplify the proportion of distances between classes isolated by distances to each class.

The target of applying the LDA is to search for decreasing the dimension dependent on discriminative features also to discover bases for projection that limit the intra-class variety yet to keep the between class variety.

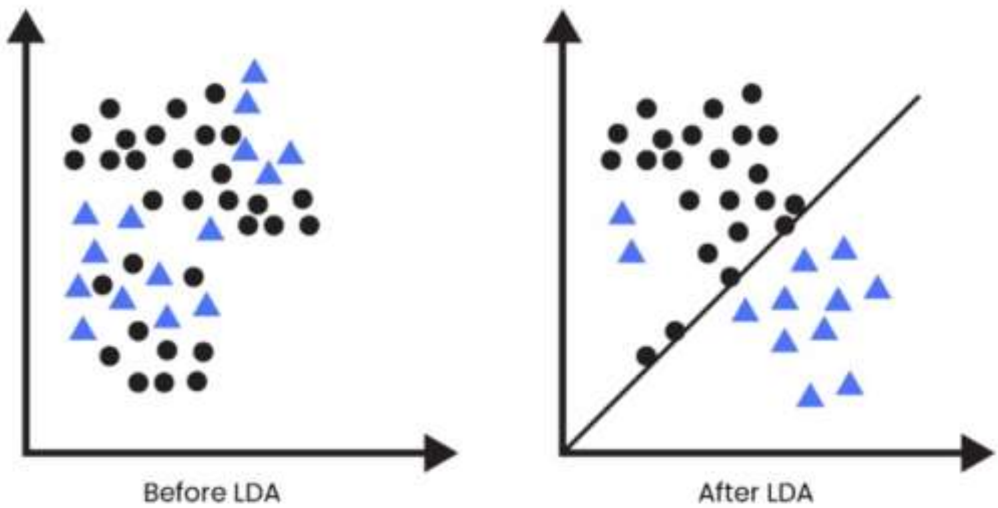


Figure 7 LDA separation between classes.

LDA looks for these vectors in the basic space that best segregate among classes (as opposed to those that best depict the information). furthermore, given various autonomous highlights comparative with which the information is portrayed, LDA makes a linear mix of these which gives the highest average differences among given classes.

Fisher face method is gotten from the Fisher linear discriminant, which depend on class explicit data. By characterizing various classes with various measurements, the pictures in the learning set are separated into the relating classes. Then, at that point, strategies like those utilized in Eigenface calculation are obtained. Fisher face method brings about a higher precision rate in autonomous part tomahawks [28]. Every axis is a direction derived according to PCA.

Fisherface acquire the benefit of reducing the dimension just as keeping the biggest variety after projection. Fisherface algorithm expands the scattering with the entire training given thus, it is required to work effectually under perfect situations, it might give different results under variety in lighting heading. The reason is that the data referring to a similar class may not be very much clearly classified in the projection space or might be spread with one another. Fisherface amplifies the class difference just as limits the inside class differences.

The LDA is considered as a superior option compared to PCA. It explicitly gives segregation among the classes, while PCA manages the information completely, without giving consideration for the fundamental construction. In fact, the primary point of the LDA comprises in discovering a base of vectors giving better discrimination among the classes.

Fisherface method utilize LDA to search for measurement decrease dependent on separation reason just as to discover bases for projection that limits the intra-class variety yet keep the between class variety. Fisherface attempts to "shape" the disperse to make it more dependable for characterization. Since it is anything but a class explicit methodology in its work. It should be realized that in Fisher calculation PCA is mentioned to be as a starter step to diminish the dimensionality of the given space, and afterward the LDA to the subsequent space, to play out the genuine class.

Here is the fisher calculation which gives an effective outcome in face recognition:

X is a normal vector with number of n classes

$$X=[X_1, X_2, \dots X_n],\ X_i = [x_1, x_2, \dots, x_m]$$

Equation 5

μ is the whole average

$$\mu = \frac{1}{N}\sum_{i=1}^{N} xi$$

Equation 6

And μ_i is the average mean of i from n classes

$$\mu_i = \frac{1}{|Xi|}\sum_{xj \in Xi} x_j$$

Equation 7

then we obtain the scattering matrix S_B

$$S_B = \sum_{i=1}^{n} N_i (\mu_i - \mu)(\mu_i - \mu)^T$$

Equation 8

And the Scattering matrix S_W

$$S_W = \sum_{i=1}^{c}\sum_{xj \in X_i} N_i (x_j - \mu_i)(x_j - \mu_i)^T$$

Equation 9

After that, the aim is to find the projection W, that expands the class separation model

$$W_{proj} = arg\ \max_W \frac{|W^T S_B W|}{|W^T S_W W|}$$

Equation 10

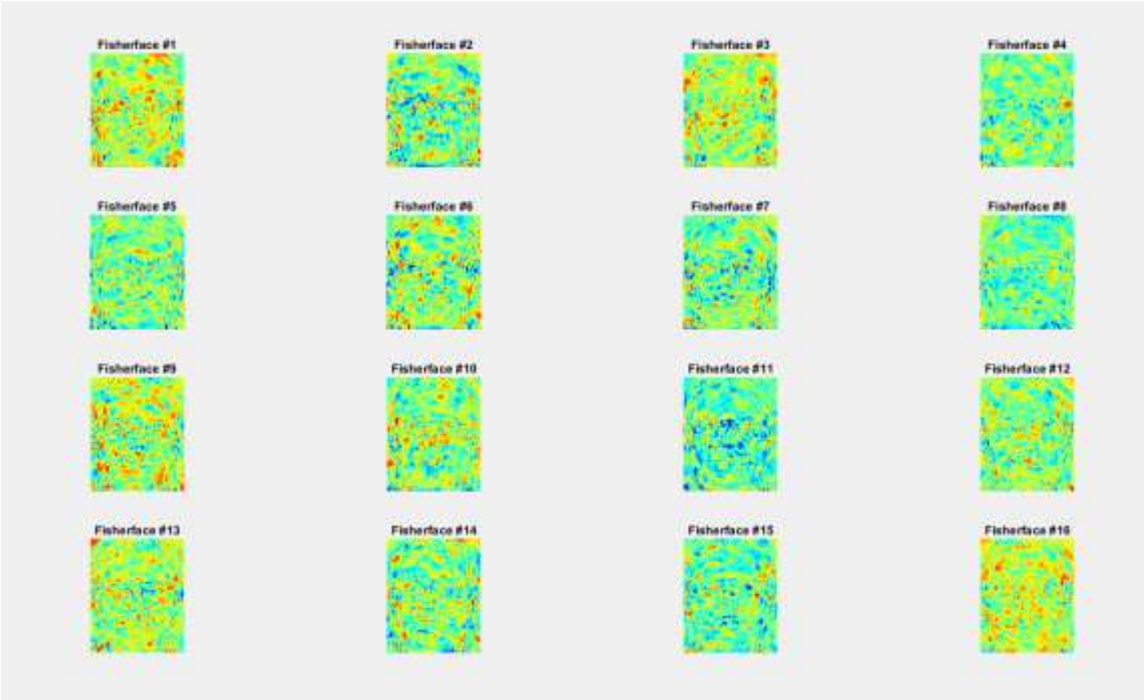


Figure 8 Fisherface obtained from 16 sample images.

Eigenfaces technique and Fisherface adopt an all-encompassing strategy to establish identification. You deal your information as a vector someplace in a high-dimensional picture space. We realize higher dimensionality is not wanted, that is why a lower dimensionality subspace was made, when most likely helpful data is saved. Eigenface approach boosts the absolute scattering, of course that can prompt issues if the fluctuation is created by another origin, since segments with a high covariance over all classes are not valuable to be classified. Therefore, to protect the discriminative data we reach the approach of LDA and enhance it as we saw in Fisherface approach. Fisherface technique did very well, considering almost perfect image situation.

Presently genuine is not that great. You basically could not ensure ideal lighting conditions in your pictures or 10 unique pictures of an individual, though, imagine a scenario where there is just one picture for every individual. Our covariance gauges for the subspace might be appallingly off-base, also will the acknowledgment. Recollect the eigenfaces technique had a 96% accuracy portion on the AT&T faces data set, how many number of pictures do we really have to get such valuable estimations. Here are the acknowledgment portions of the Eigenface and Fisherface techniques on the AT T Faces dataset, which is a genuinely simple pictures information dataset

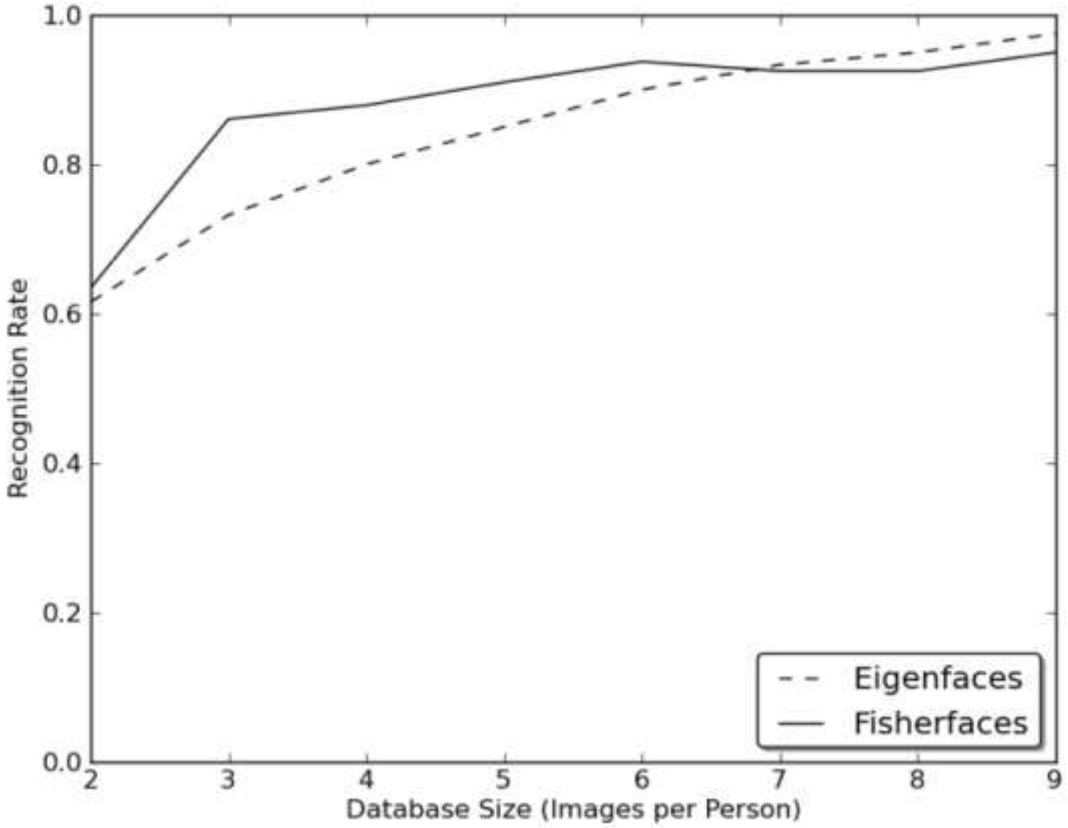


Figure 9 Recognition Rate of Eigenface and Fisherface Approaches using ATT datasets.

C. Local Binary Pattern LBP

The LBP function is utilized to explain the differentiation data of a pixel according to its neighbors. The main LBP function is characterized by window of 3*3. taking the middle pixel amount to be considered threshold of this pattern, it differentiates among the grey worth of the neighboring 8 pixels. In case that the neighboring pixel amount is higher than or the same as the middle pixel amount, the worth of pixel place is set to be 1, but if it was lower than neighboring pixel amount it will be set as 0.

$$S(\mathrm{x}) = [1 \text{ if } \mathrm{x} \geq 0\, ;\, 0 \text{ if } \mathrm{x} < 0]$$

Equation 11

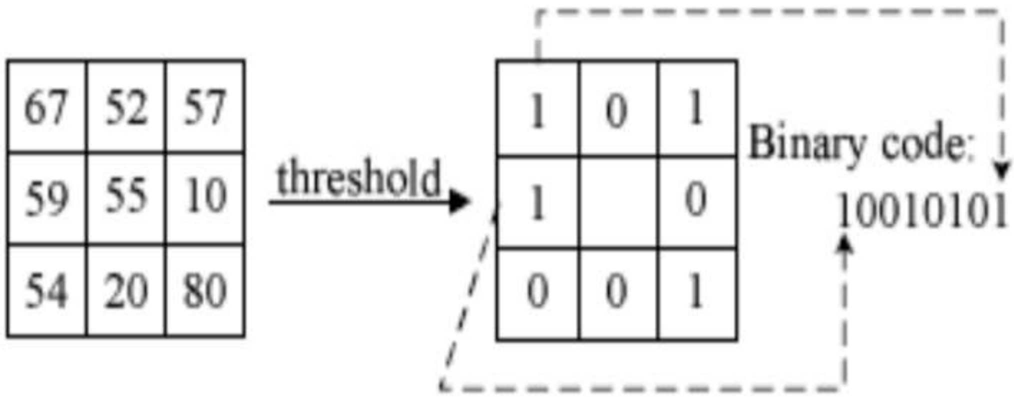


Figure 10 Basic LBP function.

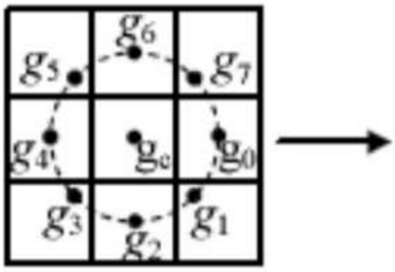
Along these lines, the 8 values in the 3*3 neighbor matrix area are differentiated to give the binary number of 8 digits. Then we are changing it over to decimal numbers, though the LBP worth of the middle number of the matrix is calculated, which is utilized to mirror the surface feature of the locale.

Because of a fixed surrounding neighboring neglects to encode data which varies in scaling. that is why the function was optimized to utilize a non-linear neighbor. The thought is to adjust a several neighboring values using a radius on a circle path, that helps to take the useful neighbors.

$$LBP_{p,r} = \sum_{p=0}^{P-1} 2^{P} s(g_p - g_c)$$

Equation 12

This LBP calculation utilized to be a circular round LBP function. g_p is to be the grey worth of the P neighbors around the pixels c. For every pixel of a picture, it figures the LBP eigenvalues. Then, at that point the eigenvalues can shape a LBP feature form. The LBPH calculation utilizes the histogram of LBP as the main vector for images to be classified.



$$
\begin{aligned}
LBP_{8,1} = {} & S(g_0-g_c)2^0+S(g_1-g_c)2^1 \\
& +S(g_2-g_c)2^2+S(g_3-g_c)2^3 \\
& +S(g_4-g_c)2^4+S(g_5-g_c)2^5 \\
& +S(g_6-g_c)2^6+S(g_7-g_c)2^7
\end{aligned}
$$

Figure 11 LBP function of circular neighboring of p with radius of 1.

This takes pieces of an image into a few sub districts and takes LBP features from every pixel of sub locale, building up a factual histogram of LBP spectrum in every sub area, so that each sub locale can utilize a factual histogram to explain the entire image by various of factual histogram parts. The benefit is to decrease the mistake that the picture is not completely adjusted in a specific criterion. To optimize the ability to deal with light variations, face details variation and disposition redirection we use the median filter, a LBPH calculation dependent on pixel neighboring grey pixel median (MLBPH) which this approach was suggested. Differentiating with the LBPH calculation, the improvement of the MLBPH calculation is when the LBP eigenvalues are determined, the middle pixels were changed with the average of their local neighboring samples.

IV. **Neural Network**

Artificial intelligent neural networks have a substantial job and extraordinary efficient enhancements were made by its role in the field of machine learning and computer vision specially with its contribution in face recognition.

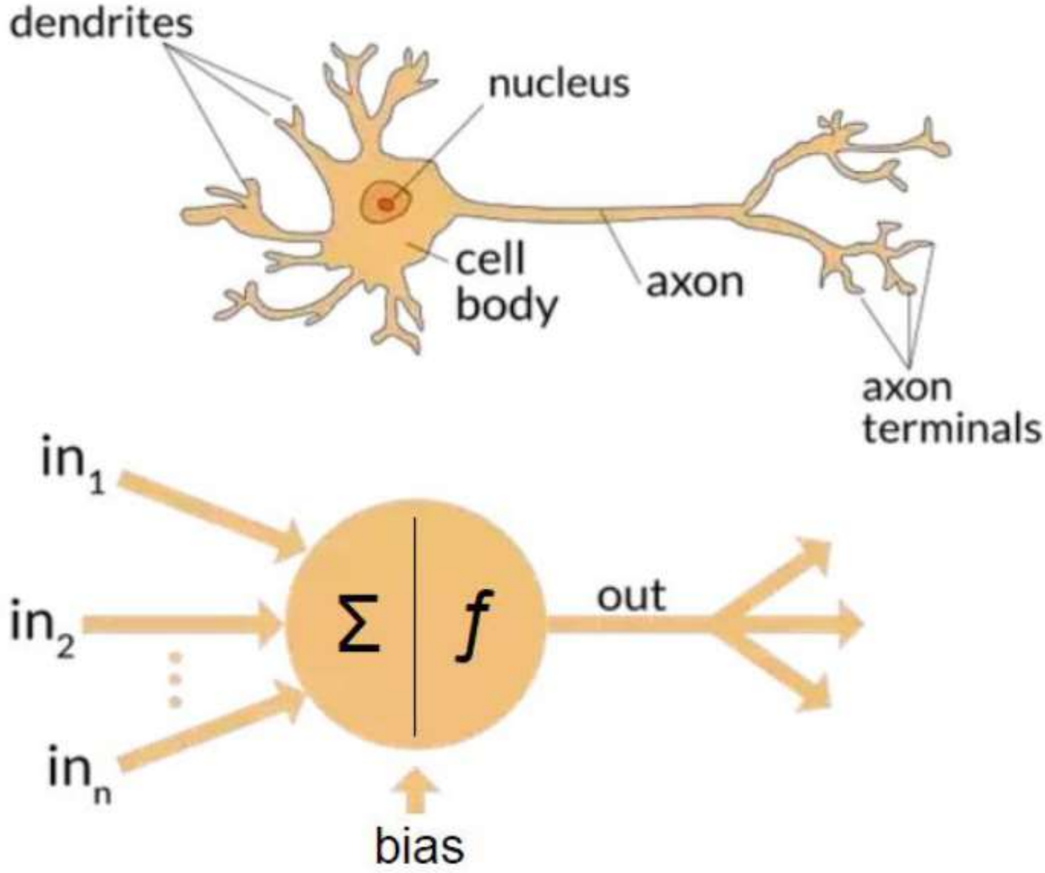


Figure 12 Neural Networks as Function and Biology.

Neural networks workflow was inspired by the mechanism of the human brain and the nervous system design of how they mutually connected, the same thing in neural networks they contain a connected neurons to give a significant output. The “memory” in neural network is important to store input data and weighted parameters and connecting nodes. The algorithm output of the function is known from the signal weighted-value, excitation function and how neurons are connected. Before convolution neural networks the previous recognition techniques depending on algorithms used to perform tasks like extracting features and choosing classifiers which needs monotonous operation, and the extracted features using algorithms cannot efficiently bring the desired output. But using convolutional neural network would show more advantages in detecting and extracting more specific features without human supervision and also has shown effectively improvement in efficiency and accuracy of face recognition.

One of the most Recent Algorithms used in face recognition which depend on convolution neural network is **DeepFace** which was presented by researchers in Facebook, It's a developed face recognition neural network using deep learning algorithms, and its process can be separated into these procedures:

1.Detection 2. Alignment 3. Representation 4. Classification

First, detect the face using Reference points detector which are the main 6 key fiducial points of the face (2 points of eyes,1 point of nose and 3 points of mouth) to prepare for alignment which are used to approximately rotate, scale and translate the image into their 6 referenced positions.

Then do the 3D alignment by applying the 67 fiducial point map with the correspondence Delaunay Triangulation on that Prepared detected face image. This was done for the alignment of the rotations plane. obtaining a 3D face model from the 2D face.

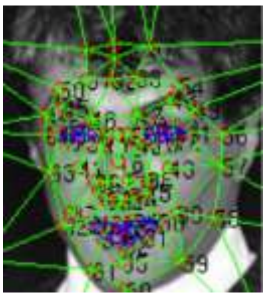


Figure 13 67 fiducial points with Delaunay triangulation.

Some corresponding residuals were added to the x-y components because it would warp to the same 3D shape. After that, frontalization was done by a piece wise affine on delaunay triangulation taken on 67fiducial points.

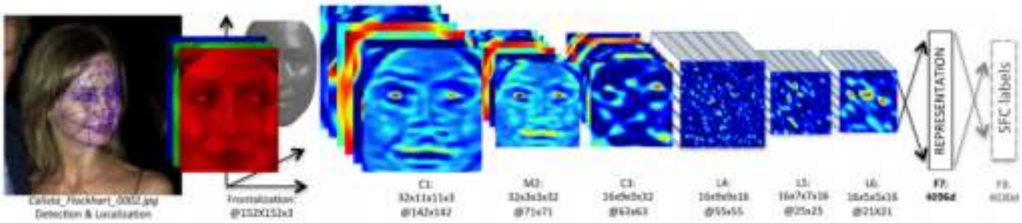


Figure 14 DeepFace Architecture.

In Representation stage the 3D-aligned colored image is sent to the convolution neural network layer with number of filters and a 3x3 max pooling layer with the stride of 2. After this one more convolution layer with some specific filters. This is important for the low-level features to be extracted from edges of the image.

Normalized DeepFace vector in this technique have multiple things in common like It have non negative values, it's very sparse, and its values are between [0, 1]. Therefore, the weighted-$\chi 2$ similarity was used:

$$\mathrm{X}^2\ (\mathcal{F}1, \mathcal{F}2) = \sum_i \omega_i \frac{(\mathcal{F}1[\mathrm{i}] - \mathcal{F}2[\mathrm{i}])^2}{(\mathcal{F}1[\mathrm{i}] + \mathcal{F}2[\mathrm{i}])}$$

Equation 13

where $\mathcal{F}1$ and $\mathcal{F}2$ are the DeepFace representations. The weight parameters are learned by a linear support vector machine, applied to vectors of the elements $(\mathcal{F}1[\mathrm{i}] - \mathcal{F}2[\mathrm{i}])\hat{}2/((\mathcal{F}1[\mathrm{i}] + \mathcal{F}2[\mathrm{i}])\ )$.

To measure the performance, we use these protocols:

In restricted protocol pair of images entered to model and the target is to check whether the image is identical or not. Unsupervised protocol indicates that the model hasn't been trained on LFW database. Unrestricted protocol indicates that more images than a single pair could access to training.

Table 2 Comparison on the LFW dataset [32].

Method	Accuracy ± SE	Protocol
Joint Bayesian [6]	0.9242 ±0.0108	restricted
Tom-vs-Pete [4]	0.9330 ±0.0128	restricted
High-dim LBP [7]	0.9517 ±0.0113	restricted
TL Joint Bayesian [5]	0.9633 ±0.0108	restricted
DeepFace-single	**0.9592** ±0.0029	unsupervised
DeepFace-single	**0.9700** ±0.0028	restricted
DeepFace-ensemble	**0.9715** ±0.0027	restricted
DeepFace-ensemble	**0.9735** ±0.0025	unrestricted
Human, cropped	0.9753	

Here, DeepFace-ensemble presents the combination of different DeepFace-single network that uses` different verification metrics. As we can conclude that DeepFace-single accuracy obtained is 97.35% accuracy.

The vision community has gained noticed improvement on face identification in unconstrained conditions lately. The mean acknowledgment exactness on LFW walks consistently towards the human exhibition of more than 97.5%. Given some extremely hard cases because of getting older impacts, huge lighting and face present varieties with LFW, any improvement over the state-of-the-art class is truly exceptional, and the framework must be made by profoundly upgraded modules. There is a solid decreasing return impact, and any advancement currently requires a significant work to diminish the quantity of errors of state of the art strategies. DeepFace gather enormous feed forward-based models with good 3D arrangement. Concerning significance of every part: 1) Without frontalization: when utilizing just the 2D arrangement, the obtained exactness is "as it were" 94.3%. Without arrangement by any means, for example, utilizing the middle harvest of face discovery, the exactness is 87.9% as portions of the facial district might drop out of the yield. 2) Without learning: when utilizing just frontalization, and a little LBP/SVM blend, the exactness is 91.4% which is as of now eminent given the effortlessness of such a classifier.

DeepID is another convolutional neural network algorithm that depend on multi convolution layers inside the baseline deep model, the multi stage training layers , pooling layer and the deep model layer for image classification. The structure of DeepID is shown in figure.5. Deep ID has a great advantage that can recognize highlevel scalable feature without losing data at the last convolution layer because of the rapidly sampling, hence improve the data integration flow.

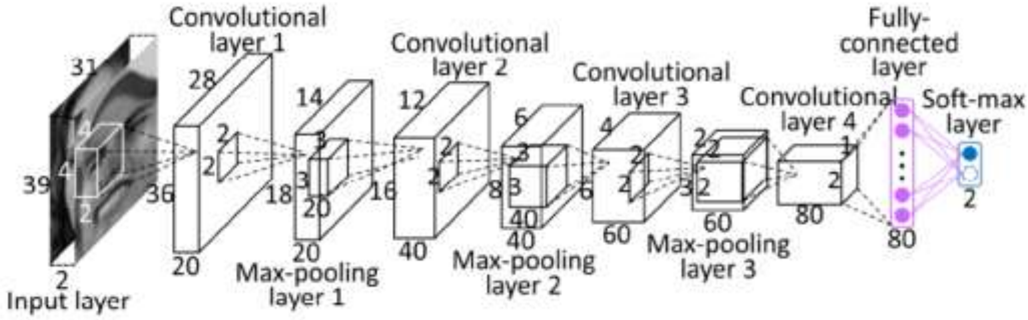


Figure 15 DeepID Structure.

Also **Facenet** considered a one of the DeepID series which depend on convolution neural networks, Face net takes the input face image and gives an output vector of 128 numbers this vector called Embedding, which contain the most discriminative feature of the face. In this Algorithm to align face patches triplets were used and generated using the online triplet mining method.

For face recognition using Facenet the only metric needs to be measured is the vector distance to make the distance of the nearest negative face image be greater than the distance of the positive face image the farthest.

V. IMPLEMENTATION

A. Used Data sets

Various techniques were introduced for identification of faces and these calculations were tested for various data sets. A considerable lot of these face information bases are openly accessible and contain face pictures with a wide assortment of postures, enlightenment points, motions, face impediments and light coloring.

Yet, these pictures have not been sufficiently commented on because of which their value for assessing the relative execution of face identification calculations is very restricted. For instance, a considerable lot of the pictures in existing data sets are not clarified with the specific posture points the moment were given. Following are depiction of a portion of face data sets.

1. ORL Data set

Refers to Olivetti Research Ltd or its also Called AT&T datasets. These face pictures were given in the period of [1992-1994] with the assistant of Cambridge university. There are around of 10 pictures of every one of 40 particular people. Pictures were given at various occasions, changing in lighting, different expressions and looks just like smiling, blinking or with glasses or not. Every one of the pictures were taken against a dim homogeneous foundation with the subjects in an upstanding, front facing state (with capacity to bear some side moving). pictures are in (.pgm) formats and size of pictures are united as a 92x112 pixels, with 256 gray levels for every pixel. For instance, here is some pictures relating to some people are displayed in this figure.

Figure 16 Some Pictures of AT&T dataset.

2. CALTECH dataset (Faces of 1999)

This face picture dataset was gathered by a researcher called Markus Weber at California Institute of Technology. It comprises of around 450 front facing face pictures to around of 26 individuals with various lighting, appearances, and position. The pictures are in .jpg format and every picture have a fixed size of 896 x 592 pixels. For instance, some of these pictures are displayed in this figure.

Figure 17 Some pictures of CALTECH dataset.

3. FEI Data set

The International Federation for Equestrian Sports (FEI) face data set has been built in the period of 2005-2006 in AI Research facility of the FEI in Sao Paulo, Brazil. And it has a bunch of face pictures, comprising of 14 unique pictures for every one of the 200 individuals shot, with head rotation from outrageous left to outrageous right with also a fixed white background, images dimensions are (640 x 480). For instance, pictures relating to a few people are displayed in this figure.

Figure 18 Some pictures of FEI dataset.

B. Experiment and Results

In this experiment we used python programming language with the benefit of OpenCV library to implement face recognition.

In this experiment, the mentioned techniques of face recognition Eigenface and LBP were tested to compare Accuracy and performance using these proposed data sets.

1. Eigenface Approach (PCA)

In this section we used the three data sets to implement face recognition using Eigenface approach. As we mentioned the data set of ORL (AT&T), CALTECH and the FEI data sets with number of individuals samples of 40, 26 and 200, respectively. We repeated the same steps each time with different number of images for each individual until we reach 10 images for each individual, as described in Table 3.

Table 3 Eigenface Experiment Results.

Data Set	Number of Individuals in Dataset	Number of images of each Individual	Amount of Images used in training	Recognation Rate (%)
ORL	40	1	40	60
		2	80	70
		3	120	75
		4	160	77.5
		5	200	77.5
		6	240	92.5
		7	280	92.5
		8	320	93
		9	360	95
		10	400	97.5
CALTECH (Face 1999)	26	1	26	32
		2	52	41
		3	78	47
		4	104	61
		5	130	61.5
		6	156	63
		7	182	79
		8	208	80
		9	234	88
		10	260	92
FEI	200	1	200	38
		2	400	48
		3	600	53
		4	800	52
		5	1000	51
		6	1200	50
		7	1400	52
		8	1600	54
		9	1800	55
		10	2000	62

Accordingly, the outcome shows that, the accuracy is a little bit weak on account of one picture for each person considering the three types of training sets.

In any case, as the quantity of training images is expanded for each individual, the accuracy additionally gets expanded and for all datasets. The RR is best for around 10 pictures for every person in training sets. In instance of more than 10 pictures for every person, the time needed for the identification increments an excess of which could not be acceptable for the ongoing application. This result shows that the RR is greatly efficient for the front facing pictures considering the AT&T and CALVET datasets. In the case of FEI face pictures datasets, the RR stays beneath the average between the other RR datasets even for the 10 pictures for every individual.

It is on the grounds that this data set have the pictures where in people have different face rotations, this would be the disadvantage of PCA technique implemented on faces that are rotated. According to the image sets type and pictures dimensions the eigenface approach would perform well.

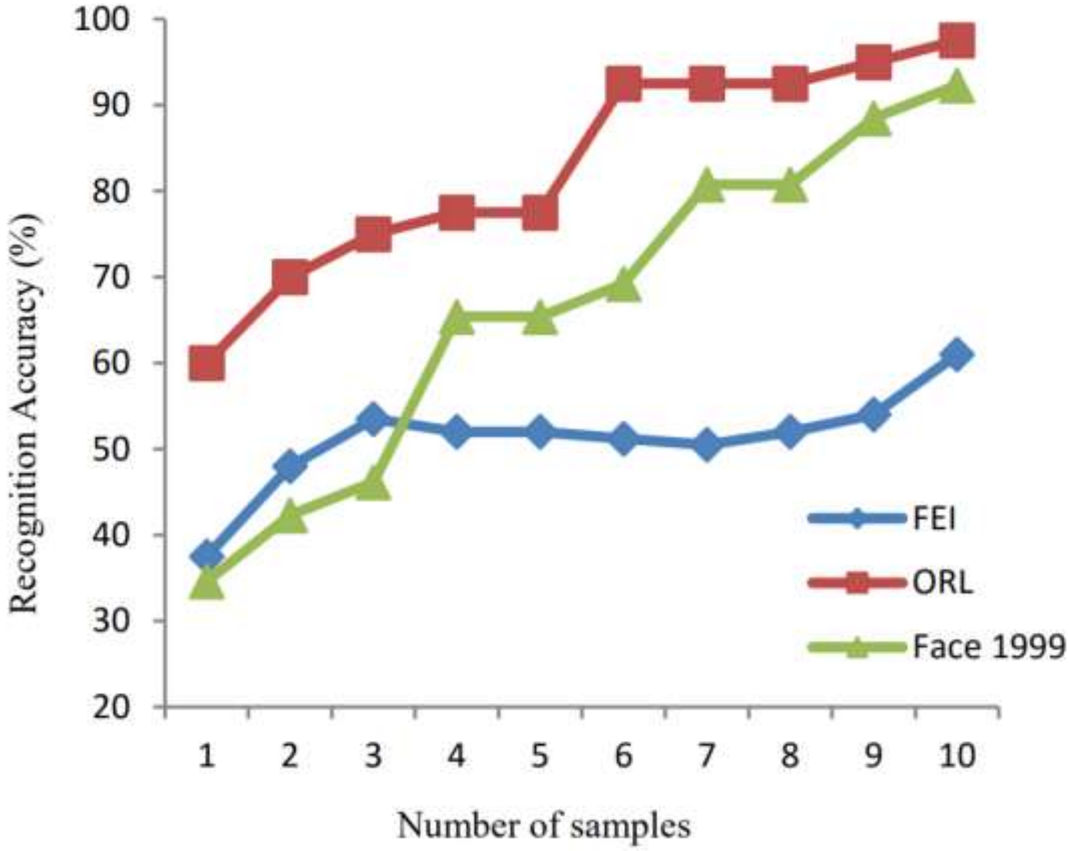


Figure 19 Recognition rate in comparison to 3 datasets.

In this experiment we used 416 images of CALTECH dataset 50% of them used for training and the other 50% are used for testing, images have different illumination conditions and different scaling. Some of these figures are shown in Figure 17. The device used in this experiment is Core i7-7700HQ with windows 10 Home Edition 64-bit Operating system with random access memory of 16GB, with Python interpreter and OpenCV library.

Table 4 Used Device Specifications.

Hardware Specifications
Processors (8 cores) Intel(R) Core(TM) i7-7700HQ CPU @ 2.8GHz Windows 10 Operating System Home Edition 64 bit 16 GB RAM

Results are shown in the table below and from Figure 20 the predictions which are correct in most cases, we can see that using Eigenface method gives a very good precision and accuracy rate that reaches 95% total accuracy with around 5 seconds of computational time using this CALTECH dataset.

Table 5 Results of Eigenface showing 10 individuals from CALTECH dataset.

	PRECISION %	**RECALL %**	**F1-SCORE %**
PERSON 1	86	100	92
PERSON 2	100	83	91
PERSON 3	100	80	89
PERSON 4	100	83	91
PERSON 5	100	100	100
PERSON 6	100	100	100
PERSON 7	86	100	92
PERSON 8	100	88	93
PERSON 9	62	100	77
PERSON 10	100	100	100
ACCURACY	95%		

In this table we measured the precision, recall and F1-score using Caltech dataset According these measurements

$$\text{Precision} = \frac{T_p}{T_p + F_p} * 100\%$$

Equation 14

$$Recall = \frac{T_p}{T_p + F_n} * 100\%$$

Equation 15

$$F_1 Score = 2 * \frac{Precision * Recall}{Precision + Recall} * 100\%$$

Equation 16

T_p (True Positive): Faces Recognized successfully.

F_p (False Positive): Faces was not recognized.

F_n (False Negative): Faces recognized wrongly.

Table 6 Confusion matrix and its parts.

		Predicted	
		Negative	Positive
Actual	Negative	True Negative	False Positive
	Positive	False Negative	True Positive

Figure 20 Prediction results of Eigenface method using CALTECH dataset.

In this experiment we used 138 images of FEI dataset 50% of them used for training and the other 50% are used for testing, images have different illumination conditions, different scaling, and also different looking angles. Some of these figures are shown in Figure 18.

Table 7 Results of Eigenface showing 10 individuals from FEI dataset.

	PRECISION %	RECALL %	F1-SCORE %
PERSON 1	80	100	89
PERSON 2	100	100	100
PERSON 3	75	75	75
PERSON 4	80	100	89
PERSON 5	75	75	75
PERSON 6	75	100	86
PERSON 7	75	100	86
PERSON 8	100	75	86
PERSON 9	100	33	50
PERSON 10	100	67	80
ACCURACY	83%		

Results are shown in the table above and from Figure 21 the predictions which are not correct in some cases, we can see that using Eigenface method do not give a very good precision and accuracy rate using the FEI dataset, because it contains images that are not aligned and has rotated faces which make not clear features to be extracted, while this process did not take too much computational time of 2 seconds because of it has less number of samples than the CALTECH dataset.

Figure 21 Prediction results of Eigenface method using FEI dataset.

2. Local Binary Pattern LBP Approach

For Implementing face recognition using LBP experiment we used a radius of 2 and neighbors of 16 a grid of (8x8). In this experiment we used 416 images of CALTECH dataset 50% of them used for training and the other 50% are used for testing, images have different illumination conditions and different scaling. Some of these figures are shown in Figure 17.

Table 8 Results of LBP showing 10 individuals from CALTECH dataset.

	PRECISION %	**RECALL %**	**F1-SCORE %**
PERSON 1	100	83	91
PERSON 2	100	80	89
PERSON 3	86	100	92
PERSON 4	100	100	100
PERSON 5	100	88	93
PERSON 6	100	100	100
PERSON 7	100	80	89
PERSON 8	62	100	77
PERSON 9	100	100	100
PERSON 10	100	100	100
ACCURACY	96%		

Figure 22 Prediction results of LBP method using CALTECH dataset.

Here we tested the CALTECH dataset with the LBP algorithm it is quite obvious that it gives a little bit better accuracy rate of 96% than Eigenface test with the same dataset, it also gives a better prediction result. Since this dataset has aligned faces and a quite perfect conditions according to illuminations and clear face features but the computational time took 283.5351 seconds for training and gathering predictions.

In this experiment we used 138 images of FEI dataset 50% of them used for training and the other 50% are used for testing, images have different illumination conditions, different scaling, and also different looking angles. Some of these figures are shown in Figure 18.

Table 9 Results of LBP showing 10 individuals from FEI dataset.

	PRECISION %	**RECALL %**	**F1-SCORE %**
PERSON 1	100	100	100
PERSON 2	100	100	100
PERSON 3	100	100	100
PERSON 4	80	100	89
PERSON 5	100	75	86
PERSON 6	67	67	67
PERSON 7	75	100	86
PERSON 8	100	100	100
PERSON 9	75	100	86
PERSON 10	100	33	50
ACCURACY	89%		

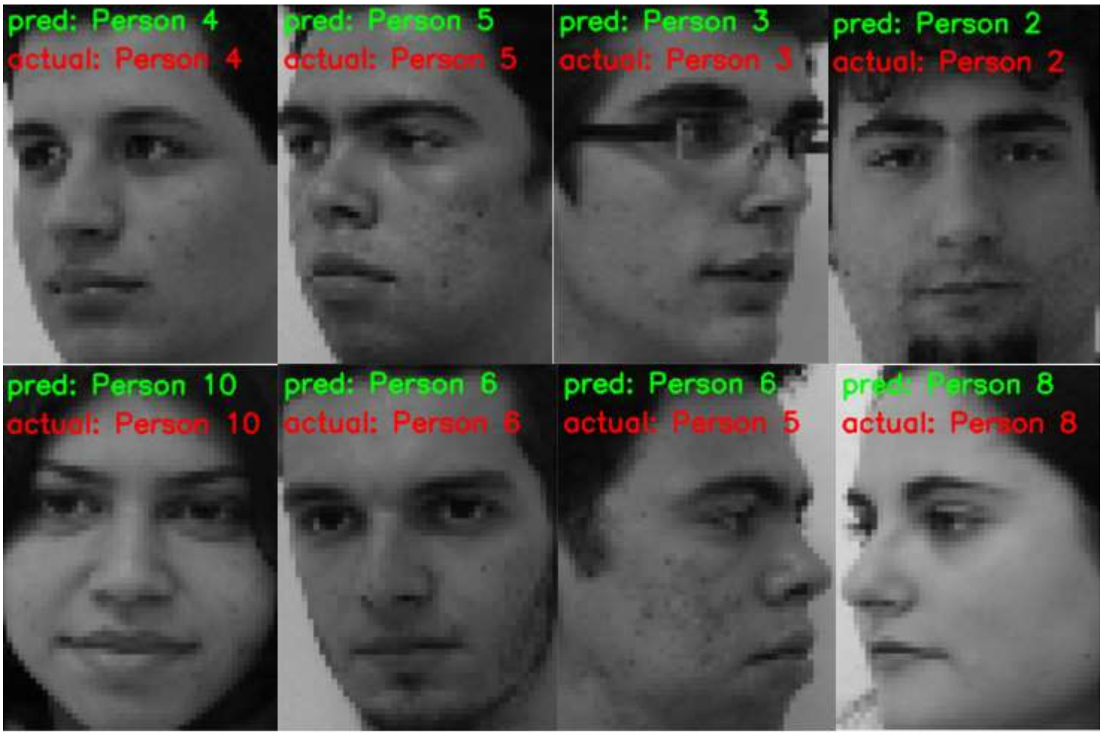


Figure 23 Prediction results of LBP method using FEI dataset.

We notice here when we used FEI dataset how the accuracy decreased because this data set contains some faces with different views and different face rotations and also it contains images with different contrast, but it has less false predictions compared to Eigenface with FEI dataset, while this process did not take too much computational time of 31.5294 seconds because of it has a smaller number of samples than the CALTECH dataset.

If we compare our results in eigen face to LBP algorithm we can find that it is not that accurate algorithm as it shows in some false predictions while the actual images are different, but in general eigenfaces is just an important algorithm to understand from a historical computer vision perspective and that is why we need to understand how these algorithms has evolve and how they eventually reached to the deep learning approaches, but deep learning modules may not always work for our particular project specially if we are considering working on a resource constrained projects like raspberry pi or an Arduino, yes we can use an accelerators or specialized models to improve speed when working on kind of projects but in some cases we need to reach back and grab some of old traditional computer vision algorithms and utilize them.

3. Comparison with three approaches

Table 10 Comparison between these approaches according ORL dataset.

Algorithm	Accuracy	Precision	Recall	F1 Score	Execution Time
EigenFace	$99\% \pm 0.87\%$	0.985 ± 0.01	0.99 ± 0.009	0.987 ± 0.010	2.74 s
FisherFace	100%	1	1	1	1.37 s
LBPH	$98\% \pm 1.24\%$	0.97 ± 0.015	0.98 ± 0.012	0.97 ± 0.015	1.84 s

In this study a comparison was made with our mentioned approaches using the AT&T dataset. Observing these results, we notice that the best accuracy gained was by the fisher face method also it has the best computational time with 1.37 seconds.

In this experiment 100 images have been used, according to these results we found the fisherface gave the best performance using the ORL dataset.

On the other hand, if we observe the results of CALTECH, we found that the best accuracy is given by LBP algorithm.

VI. CONCLUSION

A. Discussion

After observation and comparing specially with detailed methods. It became clear that traditional face recognition, compared to intelligent algorithms depending on artificial neural networks, is vulnerable to be interact by another malicious conditions, and it’s accuracy can be related to certain conditions. However, combining some traditional algorithms (like PCA and LDA algorithms), can give a higher recognition rate and accuracy. Rather Convolutional neural networks and deep learning models can give high Accuracy and high recognition rate. Just like the mentioned technique DeepFace.

Intelligent Face Recognition still has wide range of developments and improvements in deep learning algorithms and improving the research of semi-supervised learning and unsupervised learning.

In general, we really can’t beat the accuracy of deep learning model, in our traditional techniques we had some good and reasonable accuracy because of good face conditions considering lighting and controlled environments, thus these models can be fooled regarding other specific conditions like in real-time applications. For example, surveillance applications need to detect images from far distance and process the image align the face considering various conditions and then need to be recognized using some advanced techniques. Therefore, studying the Basic Approaches and making comparisons between them is the start stage of implementing a better and more effective face recognition system for real applications like depending on deep learning models and more complicated convolutional neural networks.

B. Future Work

This study helped to understand and to implement face recognition system using these presented techniques to take us a step forward for implementing a real-time application.

Next step will be studying and understanding in further details deep learning and convolution neural network which relates to facial recognition. A suggested work to do is implementing a 3D face recognition model and apply it to attendance system.Another work planned in the future is deploying face recognition model in to drone cameras to authenticate individuals to delivering letter packages, this will be made using deep learning model that can understand face emotions and can identify people with high accuracy.

VII. REFERENCES

ARTICLES

AHONEN T., HADID A., “Face description with local binary patterns: Application to face recognition”, **PAMI,** 2006.

ARSENOVIC M., SLADOJEVIC S., ANDERLA A., STEFANOVIC D., “FaceTime Deep learning based face recognition attendance system”, **IEEE 15th International Symposium on Intelligent Systems and Informatics,** 2017, Page 53–57.

BELHUMEUR P., Hespanha J., and D. K., “Eigenfaces vs. Fisherfaces: Recognition using class specific linear projection”, **IEEE TRANS. PATTERN ANALYSIS AND MACHINE INTELLIGENCE**, vol. *19*, 1997.

CAHYONO F., WIRAWAN W., FUAD Rachmadi, “Face recognition system using facenet algorithm for employee presence”, **4th International Conference on Vocational Education and Training,** ICOVET 2020, Page 57–62.

CHEN J., YI Z.”Sparse representation for face recognition by discriminative lowrank matrix recovery”, **Journal of Visual Communication and Image Representation**, 2014, vol. *25*, Page 763–773.

CHEN L., LIAO H., KO J. LIN G. Y., “A new LDA-based face recognition system which can solve the small sample size problem”, **Pattern Recognition**, vol 33, Page 1713–1726.

DAHMANE M., GAGNON L., “Local Phase-context for Face Recognition under Varying Conditions”, **Procedia Computer Science**, 2014, vol. *39*, Page 12–19.

EJAZ M. S., ISLAM M. R., SIFATULLAH M., SARKER A. “Implementation of Principal Component Analysis on Masked and Non-masked Face Recognition”, **1st International Conference on Advances in Science, Engineering and Robotics Technology**, 2019, Page 1–5.

FARAJI M., Face Recognition Under Varying Illuminations, 2015.

GREGOR K. , LECUN Y., “Emergence of complex-like cells in a temporal product network with local receptive fields” **ArXiv:1006.0448**, 2010.

GUO H. , “Face Detection With Abstract Template”, **3rd International Congress on Image and Signal Processing**, 2010.

HUANG D., LIN T., “Face Detection Based On Feature Analysis And Edge Detection Against Skin Color-like Backgrounds” **Fourth International Conference on Genetic and Evolutionary Computing**, 2010, Page 687–690.

HUANG G. “Learning hierarchical representations for face verification with convolutional deep belief networks”. ***CVPR,*** 2012.

JIANG E., “A review of the comparative studies on traditional and intelligent face recognition methods”, **Proceedings - 2020 International Conference on Computer Vision, Image and Deep Learning**, CVIDL 2020, Page 11–15.

KAK, A. M. “PCA versus LDA”, **IEEE Trans. on Pattern Analysis and Machine Intelligence**, vol. *23*, Page 228–233.

LI Y., FENG J., “Frontal face synthesizing according to multiple non-frontal inputs and its application in face recognition”, **Neurocomputing**, 2012, Page 77–85.

LIU Z. F., YOU Z. S., JAIN A. K., WANG, Y. Q., “Face detection and facial feature extraction in color image”, **Proceedings - 5th International Conference on Computational Intelligence and Multimedia Applications**, ICCIMA 2003, Page 126–130.

M. Slavkovic, “Face recognition using Eigenface approach”, **Serbian Journal of Electrical Engineering**, 2012, Page 121–130.

MD MANJURUL Ahsan, YUEQING Li, JING Zhang, MD TANVIR Ahad, “Evaluating the Performance of Eigenface, Fisherface, and Local Binary Pattern Histogram-Based Facial Recognition Methods under Various Weather Conditions”, **MDPI,** 2021.

POWERS M., David W., “Evaluation: From Precision, Recall and F-Measure to ROC, Informedness, Markedness & Correlation”, **Journal of Machine Learning Technologies,** 2011.

PREETI L., Kumar D., “Performance analysis of combination of CS with PCA and LDA for face recognition”, **IEEE International Conference on Information, Communication, Instrumentation and Control,** January, 2018, Page 1–6.

QIANG-RONG J., HUA-LAN L. “Robust Human Face Detection in Complicated Color Images. **The 2nd IEEE International Conference on Information Management and Engineering (ICIME)**, 2010, Page 218 – 221.

QU X., WEI T., PENG C., DU P., “A Fast Face Recognition System Based on Deep Learning”, **Proceedings - 2018 11th International Symposium on Computational Intelligence and Design**, ISCID 2018, Page 289–292.

SARKAR S. D., **Ajitha Shenoy** K. B., “Face recognition using artificial neural network and feature extraction”, **2020 7th International Conference on Signal Processing and Integrated Networks**, *SPIN 2020*, Page 417–422.

SCHROFF F., PHILBIN J., FaceNet: A Unified Embedding for Face Recognition and Clustering.

SEO K., KIM W., “Face Detection And Facial Feature Extraction Using Color Snake”, **ISIE 2002 IEEE International Symposium on Industrial Electronics**, Page 457–462.

SINGH C., SAHAN A. M. “Face recognition using complex wavelet moments. **Optics & Laser Technology**, 2013, vol. 47, Page 256–267.

TAIGMAN, Y. , YANG M. , RANZATO A. , WOLF L , “DeepFace: Closing the Gap to Human-Level Performance in Face Verification”, 2015.

TUMMALA N. S., SEKHAR P. C., “Face recognition using PCA and geometric approach”, **Proceedings of the International Conference on Computing Methodologies and Communication,** , January, 2018, Page 562–565.

TURK M. A., PENTLAND A. P., “Face recognition using eigenfaces”, **IEEE Computer Vision and Pattern Recognition**, 1991, Page 586–591.

WANG J., YANG H., “Face Detection Based On Template Matching And 2DPCA Algorithm”, **Congress on Image and Signal Processing**, Page 575–579.

WANG Z., SUN X., “Multiple kernel local Fisher discriminant analysis for face recognition” , **Signal Processing Journal** , 2013, Page 1496–1509.

WONG S. Y., YAP K. S., ZHAI Q., LI X., “Realization of a Hybrid Locally Connected Extreme Learning Machine with DeepID for Face Verification”, **IEEE Access**, 2019, Page 70447–70460.

YA W., BAO T., CHUNHUI D., ZHU M., “Face recognition in real-world surveillance videos with deep learning method”, **2017 2nd International Conference on Image, Vision and Computing** , *ICIVC 2017*, Page 239–

243.

ZHANG H., NASRABADI N. M., ZHANG Y., and HUANG T. S., “Joint dynamic sparse representation for multi-view face recognition” **Pattern Recognition**, 2012, vol. 45, Page 1290–1298.

ZHANG J., “Children’s Face Recognition Based on Convolutional Neural Network” , **Journal of Physics: Conference Series**, 2021, (Vol. 1744, Issue 3).

ZHAO L., “Face Detection Based On Facial Features” **ICSP**, 2006.

ZHAO X. M., WEI C. B, “A real-time face recognition system based on the improved LBPH algorithm”, **2017 IEEE 2nd International Conference on Signal and Image Processing, ICSIP 2017**, January, *2017*, Pages 72–76.

ZHAO Y., LI L., LIU Z. “A novel algorithm using affine-invariant features for posevariant face recognition”, **Computers & Electrical Engineering Journal**, 2015, Page 217–230.

ZHOU C., WANG L., ZHANG Q., and WEI X. “Face recognition based on PCA image reconstruction and LDA”, **Optik-International Journal for Light and Electron Optics,** 2013, vol. 124, Page 5599–5603.