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Eigenface and Wavelet Feature-based Face Recognition for the Development of Security System

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ABSTRACT

The security system is very crucial in our daily sphere of life. With the rapid advancement of technology and the increasing demand for secure access control systems, the development of efficient security systems has become a critical area of research. This paper represents the two significant techniques Eigenface and Wavelet feature. Eigenface utilizes Principal Component Analysis (PCA) to extract the most significant features from any facial image. However, the performance of the eigenface can be affected by various factors such as lighting, pose, and expression. To overcome this inability, we have adopted the wavelet technique. The wavelet feature extraction technique helps to extract detailed information about the image by decomposing it into different sub-bands. A comprehensive facial image of a dataset is initially collected and then the Eigenface technique is applied to extract features. The wavelet technique is also performed to recognize images as well as to identify the image having distortion to it. By imposing Wavelet features, higher accuracy, and reliability of the classifier are obtained. We hope the concept of security system development will benefit by implementing this technique.

Keywords: Security System, Eigenface, Wavelet Features, Face Recognition.

INTRODUCTION

The term security comes from the Latin secures, which means to be freedom from anxiety. The name of the security system conceals its definition. Speaking, it refers to a technique for securing something using a network of cooperating parts and tools. It refers to uniquely identifying each person using a User ID, a Particular Code, and a secret password. Today,

protecting our valuable possessions from fraud and the evil eye of criminals is crucial. Many security systems have been developed, including biometrics, CCTV, fingerprints, security alarms, face recognition, coding, password systems, cryptology, and others. Security can be categorized in many ways such as Personal security, Information security, Computer Security, Software Security, etc. The way of life of a person is protected by personal security. Information security (InfoSec) is the safeguarding of information against unauthorized access, use, abuse, modification, or destruction. Information security in the domain of digital assets is known as computer security (or cybersecurity) (software, hardware, communication systems). Software security is the science and practice of creating safe, reliable software. Asset protection is at the core of security, whether we are talking about protecting people, things, or organizations.

Eigenfaces are collections of eigenvectors used in computer vision problems for human face recognition. These wavelet coefficients are used in extracting features from hyperspectral data [1]. The wavelet transform is used to dissect the signal or pixel vector of hyperspectral data into different frequency components and then depending upon the frequency components they are used in further processing. Face recognition is an identifying tool for securing any important area or place from unwanted harm from anyone. Here, we have adopted this technique for our study. It has been used for decades and has grown to be a well-liked security system worldwide. However, adoption has become more pervasive recently.

The adoption of face recognition as a security system is not only for security and safety. The retail, transportation, hospitality, and banking industries are starting to use facial recognition [2]. What precisely is facial recognition? The answer to the question reveals that it is a biometric tool, similar to other widely used biometric technologies like fingerprint, iris, and finger vein recognition. Based on specific physiologic characteristics, facial recognition can recognize a person. It aids in the security of sensitive information and only permits authorized individuals to enter a specific location. The face is a complex, multidimensional, and significant visual stimulus. The disparate image qualities, emotions, and facial expressions complicate the issue. A facial recognition system's two major purposes are identification and verification. Face verification refers to a 1:1 match between a claimed individual's face and a template face image. Face identification is the process of matching a query face image to each image template in a face database using the 1: N problem [3].

In this study, we have adopted two methods and compared them with the accuracy level for face recognition. The methods are eigenface recognition and wavelet-based recognition. We hope that the wavelet-based recognition has a significant accuracy than the Eigenface method. According to the accuracy level, we will be able to implement a better method for security purposes. Face recognition technology is highly beneficial as the face is associated with its owner, except in identical twins. It helps to secure very confidential things as well and it allows only accessible persons who have permission to get entry to a definite place. Face recognition is fundamental in the security system because every person faces many structural differences. It can be a unique element used to recognize the same person. Again, it has versatile uses in a highly secured system. The paper is organized into Section 2: Literature Review, Section 3: Methodology, Results are presented in Section 4 and Conclusion is drawn in Section 5.

LITERATURE REVIEW

Face is a medium for recognizing the identity of anyone. The human face has a complex and dynamic structure. Using a person's face, facial recognition technology to identify or match them to their identity. It's been over 50 years of finding various methods to recognize a face. With the work of Bledsoe et.al in the 1960s, face recognition began to emerge [4]. Bledsoe created the first semi-automated face recognition system to identify facial characteristics on images, including the eyes, ears, nose, and mouth. They utilize computers to begin their idea of face recognition. However, much of their work was never able to publish due to an unnamed intelligence agency.

In the 1970s, Goldstein et.al automated the recognition using 21 distinct subjective criteria, such as hair color and lip thickness [5]. The researchers approached with the hope of defining the face they used the geometric features of the face as a set of parameters to do some pattern recognition. A formal technique that leaves a distinctive sign in the way of face recognition was established by Sirovich et al. [6]. The principal component analysis (PCA) was used by Sirovich and Kirby (1987) to define the geometry of the faces [7]. In 1991, Pentaland and Turk presented an example of facial recognition technology [8]. They used the Eigenfaces technique with the PCA. After that, to encourage the industry and the academy to move forward on this topic, the Defense Research Projects Agency (DARPA) developed the Face Recognition Technology program, which provided the world with a sizable, challenging database composed of 2400 images for 850 persons.

In order to promote and advance face recognition technology to support facial recognition projects namely the Face Recognition Grand Challenge (FRGC) which was established in 2005 by the U.S. Government. Facebook started integrating facial recognition technology in 2010. This technology recognizes people whose faces could appear in the daily updates of images on Facebook. With the introduction of the iPhone X, Apple introduced a facial security system known as Face ID. In recent years, deep learning methods such as convolutional neural networks (CNNs) have achieved state-of-the-art results on face recognition tasks. Face Net, introduced by Schroff et al. in 2015, is a deep learning-based face recognition system that uses a triplet loss function to learn a face embedding space [9].

Adversarial attacks have been studied in the context of face recognition to evaluate the robustness of face recognition systems to attacks. In 2018, Sharif et al. demonstrated that adding imperceptible perturbations to a face image can cause a deep learning-based face recognition system to misclassify the image [10]. The use of face recognition in law enforcement and surveillance has raised many privacies and ethical concerns. Researchers have studied the potential for bias and discrimination in face recognition systems, as well as the legal and ethical implications of their use. In 2018, Buolamwini and Gebru used face recognition for gender shades intersectional accuracy disparities in commercial gender classification [11]. Facial recognition technology is still evolving quickly, and its applications are expanding rapidly day by day.

METHODOLOGY

A face recognition system is referred to as a technology that is specially designed to spontaneously verify a person's identity by analyzing the facial structures of that person against a database of known persons. The proposed face recognition approach consists of several steps that are presented in Fig. 1 as a systematic flowchart. Sequential descriptions of the proposed methodology are described in the following subsections.

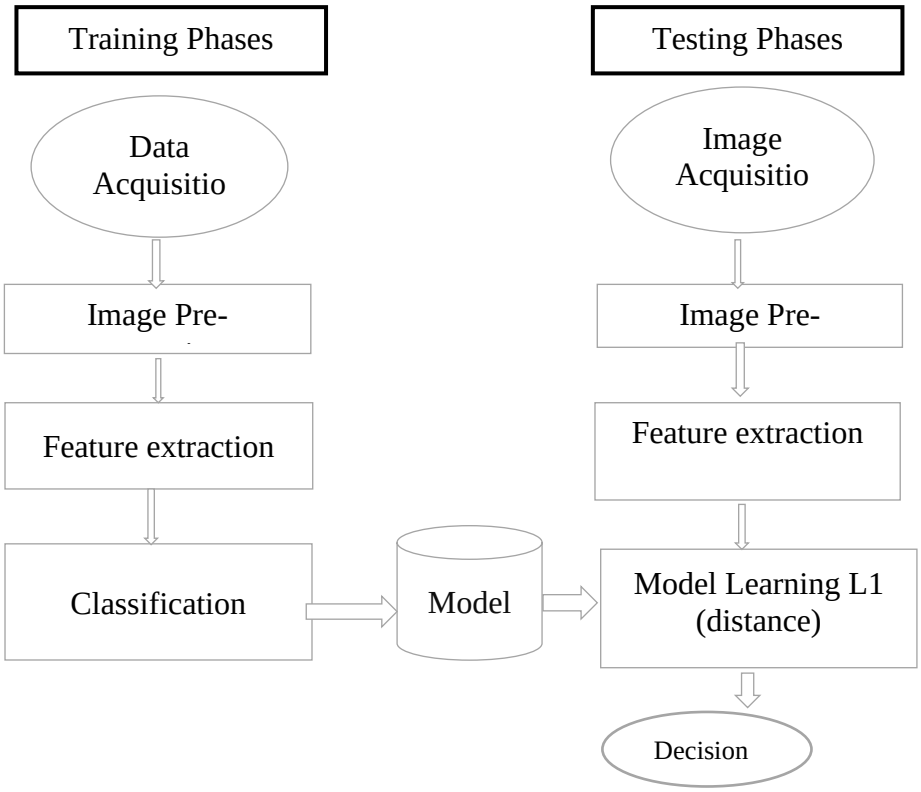


Figure 1: Systematic Flowchart of the Proposed Methodology

Image Preprocessing

In order to handle face recognition more efficiently, a non-frontal facial can be transformed into a frontal posture using a number of approaches called face normalization [12]. After data acquisition to remove the noise and light effects, and adjusting the scaling and the rotation effect, the face images will be normalized before being sent to the face recognition module. The input image is scaled to 180×200 pixels and transformed to grayscale using the following equation.

$$G_{ri} = \frac{R_i + G_i + B_i}{3}, \quad \text{i=1, ..., M} \times \text{N} \tag{1}$$

where, G_{ri} is the grayscale value of i^{th} image. R_i, G_i and B_i correspond to the red, green, and blue value of the i^{th} image. The generated images are scaled using a linear interpolation approach.

To denoise the gray images using wavelet transforms which are described in the following subsections.

Image Decomposition using 2D-DWT

In our study, the given images called input images are reduced in low-frequency images by applying wavelet transform and avoiding the high-frequency images. Discrete Wavelet Transform (DWT) is frequently used in signal processing to represent a signal $f(t)$ [13]. Two-dimensional discrete wavelet transformation of $m \times n$ image is defined as the following

$$DWT(i,j,k,h) = \frac{1}{\sqrt{2^i}} \sum_{k=0}^{m-1} f(x) \varphi\left(\frac{x}{2} - k\right) + \frac{1}{\sqrt{2^i}} \sum_{h=0}^{n-1} f(y) \varphi\left(\frac{y}{2} - h\right) \quad (2)$$

Where i and j are the power of binary scaling, k and h are constants of the filters. Multiresolution, which is characterized by a two-channel filter bank that regulates information loss across resolutions, is similar to the one-dimensional wavelet transform of a signal in that it is often used to approximate images at various resolutions using orthogonal projections. In image decomposition, 1-level decomposition divides the original image into four sub-hands known as Low-low (LL), High-low-(HL), Low-high (LH), and High-high (HH), which roughly correspond to horizontal, vertical, and diagonal features [14]. An example of a two-level decomposition of an image is presented in Fig. 2.

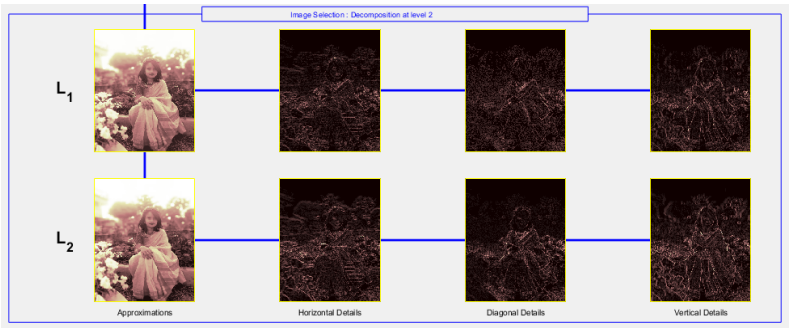


Figure 2: 2D-DWT of level 1and 2

Daubechies Wavelet

Daubechies are supported orthogonal wavelets and found application in DWT. This wavelet has a unique scaling confinement. It can be exploited to decompose the real signal, remove the noise part (details), and then re-decomposed [15]. The mathematical formulation of the Daubechies wavelet is written as

$$\psi(t) = \sqrt{2} \sum_{k=0}^{N-1} (-1)^k C_K \psi(2t - k) \quad (3)$$

The scaling function of the Daubechies wavelet $\varphi(t)$ is denoted as

$$\varphi(t) = h(0)\sqrt{2}\varphi(2t) + h(1)\sqrt{2}\varphi(2t-1) + h(2)\sqrt{2}\varphi(2t-2) + h(3)\sqrt{2}\varphi(2t-3) + h(4)\sqrt{2}\varphi(2t-4) \quad (4)$$

The wavelet function is denoted as $\Psi(t)$ and expressed as

$$\Psi(t) = g(0)\ \sqrt{2}\ \varphi(2t) + g(1)\ \sqrt{2}\ \varphi(2t-1) + g(2)\varphi(2t-2) + g(3)\varphi(2t-3) + g(4)\varphi(2t-4) \quad (5)$$

The Daubechies wavelets are an orthogonal wavelet family that defines a discrete wavelet transform. It is distinguished by having a maximum number of vanishing moments for a particular support. There is a scaling function known as the father wavelet associated with each wavelet type in this class that produces an orthogonal multiresolution analysis. The images decompose into up to five layers using the Daubechies wavelet order N (dbN) to create fusion images [16]. In this study, we have used the db10 to decompose the collected images. After that, the PCA has been utilized to extract the features from the decomposed images.

Principal Component Analysis (PCA)

Principal Component Analysis is a very familiar approach to face recognition. The PCA is an algorithm that represents the face images into components known as eigenfaces. This technique reduces the number of variables that must be considered when data are acquired [17]. As a consequence, the variables are broken down into smaller parts. By recovering as much variance from the original data as feasible, the primary goal of PCA is to decrease the dimensionality of the data set [18]. To explain the PCA method, let us consider the set of *M* training images $\Gamma_1, \Gamma_2 \ \ldots\ \ldots\ \Gamma_M$. The average face can be expressed as

$$\Psi = \frac{1}{M}\sum_{i=1}^{M}\Gamma_i \quad (6)$$

Each face is separated from the average by the following vector

$$\varphi_i = \Gamma_i - \Psi \quad (7)$$

where, the difference between each image and the average is denoted by φ_i. The co-variance matrix is calculated by the equation (8).

$$C = \frac{1}{M}\sum_{i=1}^{M}\varphi_i.\varphi_i^T = A.A^T \quad (8)$$

where, $A = [\varphi_1, \varphi_2, \ \ldots\ \ldots\ \varphi_M]$ then, a set of *M* orthonormal vectors $u_1, u_2, u_3, \ \ldots\ \ldots\ u_M$ are sought using principal components on this collection of large vectors. The face image is translated into its eigenface components projected onto the face space by a straightforward operation in order to get a weight vector Ω representing the contributions of different eigenfaces to a facial image Γ.

$$\omega_k = u_k^T(\Gamma - \Psi) \quad (9)$$

where, ω_k is the weight contribution of each eigenface. We select k -most important eigenvector for k largest eigenvalues. The weight vector is

$$\Omega = \left[\omega_1, \omega_2, \ \ \ldots \ldots \ \omega_M\right] \tag{10}$$

It uses the eigenfaces as a foundation set for face images and illustrates how each eigenface contributes to portraying the face images. The Euclidean distance has been measured to classify the features in the entire database that are nearest in similarity. In this way to determine which face best describes an unknown input facial image is to locate a representation of k that reduces the Euclidean distance ε_k .

$$\varepsilon_k = \| \Omega - \Omega_k \|^2 \tag{11}$$

where, Ω_k is a weight vector describing the k^{th} face from the training dataset. When ε_k is less than a certain threshold ε , a face is designated as belonging to person k ; otherwise, the face is listed as unidentified. The method works by mapping known face images into a feature space that encompasses their substantial variances. A specific face can be recognized by simply comparing its weights to those of other known persons. The projection operation defines an individual face as a weighted sum of its eigenface features. The subject from the training set whose feature vector is closest within allowable thresholds is matched to the input image. After that, the Eigenface technique is utilized to recognize the face from the facial images.

Face Recognition Using Eigenface Technique

Holistic or appearance-based techniques transfer the entire face area to a lower dimensional subspace using a linear or non-linear algorithm. Eigenfaces, one of the earliest effective techniques, was proposed by Turk and Pentland [19]. In the eigenface method, PCA is also used in both face recognition and detection [20]. Eigenfaces are collections of eigenvectors used in computer vision problems for human face recognition. Eigenvectors are considered to make the features for the variation in characteristic images. The eigenvectors of each image create a pale or face mask. The PCA technique is used in this eigenface approach to project the space of images into a low-dimensional space. After that, to calculate the eigenface, it can be computed eigenvalues and eigenvectors from the covariance matrix *C* [21].

Step 1: Obtain face images $I_1, I_2, I_3, \ldots, I_m$ as training dataset faces. Consider m=4 and size of each image $N \times N$ here consider N=2. Image matrix

$$I_1 = \begin{bmatrix} 1 & 1 \\ -2 & -3 \end{bmatrix}_{2\times 2} \qquad I_2 = \begin{bmatrix} 1 & -1 \\ 3 & 2 \end{bmatrix}_{2\times 2} \tag{12}$$

$$I_3 = \begin{bmatrix} 2 & -2 \\ 1 & 3 \end{bmatrix}_{2\times 2} \qquad I_4 = \begin{bmatrix} 1 & 2 \\ 2 & 1 \end{bmatrix}_{2\times 2} \tag{13}$$

Step 2: We have to Represent every image I_i as a vector Γ_i and there obtain an image vector represented by Γ_i will be used in all the steps for calculation.

$$\Gamma_1 = \begin{bmatrix} 1 \\ -2 \\ 1 \\ -3 \end{bmatrix}_{N^2 \times 1} \qquad \Gamma_2 = \begin{bmatrix} 1 \\ 3 \\ -1 \\ 2 \end{bmatrix}_{N^2 \times 1} \tag{14}$$

$$\Gamma_3 = \begin{bmatrix} 2 \\ 1 \\ -2 \\ 3 \end{bmatrix}_{N^2 \times 1} \qquad \Gamma_4 = \begin{bmatrix} 1 \\ 2 \\ 2 \\ 1 \end{bmatrix}_{N^2 \times 1} \tag{15}$$

N=2, M=4 (training set of M image of size $N \times N$)

$$\psi = \frac{1}{M} \sum_{i=1}^{m} \Gamma_i \tag{16}$$

Step 3: Mean face vector

$$\psi = \frac{1}{4} \begin{bmatrix} 1+1+2+1 \\ -2+3+1+2 \\ 1-1-2+2 \\ -3+2+3+1 \end{bmatrix} = \frac{1}{4} \begin{bmatrix} 5 \\ 4 \\ 0 \\ 3 \end{bmatrix} = \begin{bmatrix} \frac{5}{4} \\ 1 \\ 0 \\ \frac{3}{4} \end{bmatrix} \tag{17}$$

Step 4: Difference between each image and the average

$$\Phi_i = \Gamma_i - \Psi \tag{18}$$

$$\Phi_1 = \begin{bmatrix} 1 \\ -2 \\ 1 \\ -3 \end{bmatrix} - \begin{bmatrix} \frac{5}{4} \\ 1 \\ 0 \\ \frac{3}{4} \end{bmatrix} = \begin{bmatrix} \frac{-1}{4} \\ -3 \\ 1 \\ \frac{-15}{4} \end{bmatrix} = \frac{1}{4} \begin{bmatrix} -1 \\ -3 \\ 1 \\ -15 \end{bmatrix}$$

$$\Phi_2 = \begin{bmatrix} 1 \\ 3 \\ -1 \\ 2 \end{bmatrix} - \begin{bmatrix} \frac{5}{4} \\ 1 \\ 0 \\ \frac{3}{4} \end{bmatrix} = \begin{bmatrix} \frac{-1}{4} \\ 2 \\ -1 \\ \frac{5}{4} \end{bmatrix} = \frac{1}{4}\begin{bmatrix} -1 \\ 8 \\ -4 \\ 5 \end{bmatrix}$$

$$\Phi_3 = \begin{bmatrix} 2 \\ 1 \\ -2 \\ 3 \end{bmatrix} - \begin{bmatrix} \frac{5}{4} \\ 1 \\ 0 \\ \frac{3}{4} \end{bmatrix} = \begin{bmatrix} \frac{3}{4} \\ 0 \\ -2 \\ \frac{9}{4} \end{bmatrix} = \frac{1}{4}\begin{bmatrix} 3 \\ 0 \\ -8 \\ 9 \end{bmatrix}$$

$$\Phi_4 = \begin{bmatrix} 1 \\ 2 \\ 2 \\ 1 \end{bmatrix} - \begin{bmatrix} \frac{5}{4} \\ 1 \\ 0 \\ \frac{3}{4} \end{bmatrix} = \begin{bmatrix} \frac{-1}{4} \\ 1 \\ 2 \\ \frac{1}{4} \end{bmatrix} = \frac{1}{4}\begin{bmatrix} -1 \\ 4 \\ 8 \\ 1 \end{bmatrix}$$

$$C = \frac{1}{M} AA^T$$

Step 5: Find the Covariance matrix

$$A = \begin{bmatrix} \frac{-1}{4} & \frac{-1}{4} & \frac{3}{4} & \frac{-1}{4} \\ -3 & 2 & 0 & 1 \\ 1 & -1 & -2 & 2 \\ \frac{-15}{4} & \frac{5}{4} & \frac{9}{4} & \frac{1}{4} \end{bmatrix}_{N^2 \times M} \tag{19}$$

$$A^T = \begin{bmatrix} \frac{-1}{4} & -3 & 1 & \frac{-15}{4} \\ \frac{-1}{4} & 2 & -1 & \frac{5}{4} \\ \frac{3}{4} & 0 & -2 & \frac{9}{4} \\ \frac{-1}{4} & 1 & 2 & \frac{1}{4} \end{bmatrix}_{M \times N^2} \tag{20}$$

For simplicity we calculate $A^T A$, Matrix size $M \times N^2$, $N^2 \times M$

Consider eigenvectors v_i of $A^T A$

$$(A^T A)v_i = \mu_i v_i$$

Multiply A on both side

$$AA^T Av_i = \mu_i Av_i$$
$$(AA^T)u_i = \lambda_i u_i$$

Where,

$$Av_i = u_i \ \& \ \lambda_i = \mu_i$$

AA^T & $A^T A$ have same eigenvalues.

$$AA^T = \begin{bmatrix} \frac{3}{4} & 0 & -2 & \frac{9}{4} \\ 0 & 14 & -3 & 14 \\ -2 & -3 & 10 & -9 \\ \frac{9}{4} & 14 & -9 & \frac{83}{4} \end{bmatrix} \quad (21)$$

$$C = \frac{1}{M} AA^T = \frac{1}{4} \begin{bmatrix} \frac{3}{4} & 0 & -2 & \frac{9}{4} \\ 0 & 14 & -3 & 14 \\ -2 & -3 & 10 & -9 \\ \frac{9}{4} & 14 & -9 & \frac{83}{4} \end{bmatrix} \quad (22)$$

$$C = \begin{bmatrix} 0.1875 & 0 & -0.5 & 0.5625 \\ 0 & 3.5 & -0.75 & 3.5 \\ -0.5 & -0.75 & 2.5 & -2.25 \\ 0.5625 & 3.5 & -2.25 & 5.1875 \end{bmatrix}$$ = Covariance Matrix

Step 6: Compute eigenvalues and eigenvectors from the covariance matrix C. We must have to normalize eigenvectors. Normalized eigenvectors are called eigenfaces of the training images.

$$\lambda_1 = 0 \quad , \quad \mathrm{v}_1 = \begin{bmatrix} -3 \\ -1 \\ 0 \\ 1 \end{bmatrix} \quad \text{eigenvector } \mathrm{u}_1$$

$$\lambda_2 = 0.374 \quad , \quad \mathrm{v}_2 = \begin{bmatrix} 0.636 \\ -0.907 \\ 0.888 \\ 1 \end{bmatrix} \quad \text{eigenvector } \mathrm{u}_2$$

$$\lambda_3 = 0 \quad , \quad \mathrm{v}_3 = \begin{bmatrix} 4.678 \\ -13.035 \\ -17.783 \\ 1 \end{bmatrix} \quad \text{eigenvector } \mathrm{u}_3$$

$$\lambda_4 = 0 \quad , \quad \mathrm{v}_4 = \begin{bmatrix} 0.092 \\ 0.725 \\ -0.451 \\ 1 \end{bmatrix} \quad \text{eigenvector } \mathrm{u}_4$$

Must Normalize eigenvectors mean magnitude of eigenvector $\| u_i \| = 1$

$$\begin{aligned} \| v_1 \| &= \sqrt{(-3)^2 + (-1)^2 + 0 + 1^2} = \sqrt{12} \\ \| v_2 \| &= \sqrt{0.41 + 0.83 + 0.79 + 1} = \sqrt{3.03} \\ \| v_3 \| &= \sqrt{21.9 + 170.04 + 316.13 + 1} = \sqrt{509.07} \\ \| v_4 \| &= \sqrt{0.01 + 0.52 + 0.20 + 1} = \sqrt{1.73} \end{aligned} \tag{23}$$

Normalized eigenvectors

$$u_1 = \frac{1}{\sqrt{12}}\begin{pmatrix}-3\\-1\\0\\1\end{pmatrix} \quad , \quad u_2 = \frac{1}{\sqrt{3.03}}\begin{pmatrix}0.64\\-0.91\\0.89\\1\end{pmatrix}$$

$$u_3 = \frac{1}{\sqrt{509,70}}\begin{pmatrix}4.68\\-13.04\\-17.78\\1\end{pmatrix} \quad , \quad u_4 = \frac{1}{\sqrt{1.73}}\begin{pmatrix}0.09\\0.72\\-0.45\\1\end{pmatrix} \tag{24}$$

This is the eigenfaces of the training images

How to Reconstruct Image I_i

$$\Gamma_i = \psi + [u_1 \quad u_2 \quad \dots \quad u_m]\begin{bmatrix}w_1\\w_2\\.\\.\\.\\w_m\end{bmatrix} \tag{25}$$

Where,

$\Gamma_i = Image\ Vectors\ matrix$

$\Psi = Mean\ face\ of\ \ training\ set$

$u_i = Eigen\ face\ of\ \ the\ train\ images$

$w_i = Weight\ contribution\ of\ \ each\ eigenface.$

Any image in dataset reconstructed as

$$\Gamma_i = \psi + \sum_{i=1}^{m} u_i w_i \tag{26}$$

m=k if we select k most important eigenvector for k largest eigenvalues.

Weight (w_k)is the product of image(vector) with each of the eigenvectors.

$$w_k = u_k^T \phi_i \tag{27}$$

We can calculate the weights for the image in training dataset

$$\Omega = \begin{bmatrix} W_1 \\ W_2 \\ . \\ . \\ . \\ W_k \end{bmatrix} \tag{28}$$

Putting this value, we can get reconstruct the images I_i

To compare the test image with the different training images, Euclidean distance (ε_k) is calculated from the weight matrix Ω_{new} and each face class Ω_k .

$$\| \Omega_{new} - \Omega_k \| = \sum_{i=1}^{M} (\omega_i{}^n - \omega_i{}^k)^2 \tag{29}$$

When minimum ε_k <Threshold (T), then the test image belonging to class k, otherwise, it is unknown [22].

Face Recognition Using Combination of Wavelet and PCA Features

In this study, we have proposed a new approach based on the combination of wavelet and PCA features to recognize faces measuring L_1 distance. The Daubechies wavelet10 (db10) is adopted to extract the features vector. We resize and binarize the input images to extract the wavelet features. After that, the standard deviation (STD) is calculated according to the rows and columns. The db10 wavelet features vector is obtained by combining row- and column-wise STD. After getting the wavelet features vector, the PCA method is applied to reduce the dimension of the features. In fact, PCA extracts the most representative features from the input image feature vector.

Face recognition scheme is implemented using wavelet feature and then PCA method. Here wavelets are used to extract facial Wavelet Feature Vector. The steps are given below:

- Step-1: At first, resize the input image.
- Step-2: Binarize the given image as input.
- Step-3: After binarization of the image apply Daubechies wavelet10 (db10) for 1-level DWT.
- Step-4: Calculate the Standard Deviation (STD) according to the rows and columns.
- Step-5: Combining the row wise STD and column wise STD, finally we have obtained the Wavelet FeatureVector.

As explained in generic face recognition applications, PCA are mostly employed for two reasons. The feature vector consists of 380 points. Though it is not such a big size to store in memory but in order to make system faster and less memory to store we have to reduce the size of the vector. So, to reduce 380 points vector we are utilizing PCA. PCA extracts the most representative features from the input data such that, despite the size reduction, the primary features are still able to adequately reflect the original data. The feature mapping equation for PCA can be represented as

$$fv_{PCA} = [\, fvstd - m]P_{PCA} \tag{30}$$

where the input feature vector is *fvstd* , *m* is the mean of all feature vectors of input images, P_{PCA} is the transformation matrix and the reduced feature vector is fv_{PCA}. Mean of all features vector of total 800 images are m. Finally, we obtained the combination of wavelet and PCA feature vectors for model learning in the training and testing phases. It performs a sequential match with the first, second, and third matches of the images, and so on. The similarity is measured based on L_1 distance for training the classification model. Obviously, the best match will be one where the least distance is obtained from the test images. The L_1 distance is measured from quire (fv_q) image feature and training feature vector fv_{PCA} for *l*-label matching by

$$L_1 = \sum_{i=1}^{l}(fv_q - fv_{PCAi}) \tag{31}$$

RESULTS AND DISCUSSION

In this section, we have presented the experimental results in tabular form as well as the graphical forms and analyzed them in different aspects. The determination of the Eigen vector-based face recognition system and Wavelet-based face recognition system yielded insightful outcomes. The results from the Wavelet-based PCA feature extraction technique which extracted the features from the collected database and then classified the face and non-face images using L_1 distance measures are illustrated sequentially in this section.

Data Description and Experimental Setup

A database is created for the experimental evaluation containing 1000 images from 50 students of Khulna University, Bangladesh. Actually, we collected the images from the subjects only for this research work with the consent of the students. Each student was instructed to perform 20 different facial expressions and we obtained a total of 1000 images. For the experimentation, 80% of random images of total images are taken as a training set and 20% as a testing set. We have evaluated the experiment using the MATLAB code. Some sample images of one student among 1000 images are shown in the Fig. 3 given below.



Figure 3: Sample database images with different facial expressions

Results for Eigenface-based Recognition

At first, the experiments of the eigenface-based recognition system are processed using the collected databased. The position of each image contributes more or less an eigenvector and

these eigenvectors represent a sort of ghostly face image. The converted the face images into eigenvectors are stored the corresponding eigenvalues. In order to identify or recognize a specific image, this method first counts the eigenvalue of the given image and then compare the eigenvalue with the stored eigenvalues. The eigenvalue which matches approximately in the percentage of 95 is considered to be recognized. Finally, it recognizes the face of the image. In the Eigenface technique, an input image is identified by comparing the eigenvalue of that image to the most significant eigenvalues of the existing images. From this training model, we can obtain a good result after giving an image of a person as input having different facial expressions. For recognizing such a face, if the test image has a minimal Euclidean distance smaller than the threshold, then the image is recognized. In the test case, it can be obtained 94% recognition accuracy using images of different facial expressions. The following Fig. 4 presents two images with different facial expressions which are identified using an eigenface-based approach.

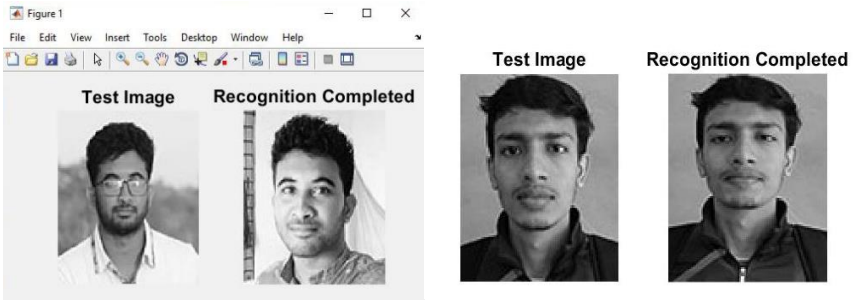


Figure 4: Eigenface based Recognition

Results for Combination of Wavelet and PCA Based Recognition

We have followed the sequential steps for wavelet-based recognition where the first stage is to convert an image inro grayscale and then binaries, that means, the preprocessing stage. A sample preprocessed images are shown in Fig. 5. At the feature extraction stage, the discrete wavelet transform as Daubichses (db10) wavelet is adopted to obtain the wavelet coefficients. After that, the standard deviation (column-wise and row-wise) are taken form the obtained db10 wavelet coefficients which are provided a combined feature vector. The PCA method is utilized to reduce the feature dimensions.



(a) **(b)**

Figure 5: (a) Original image, (b) Binarize images

In the classification stage, the mean of the images is taken to find the nearest match. We have taken input images for their closest matches in the database. It performs a sequential match with the first, second, and third matches of the images, and so on. The L_1 distance is calculated to measure the similarity with the images of the dataset. The best match is the one where the distance between input images and the images of the database is the least. The experimental information for training images is depicted in Table 1, where the four wavelet coefficients-approximation (cA), details (cD), horizontal (cH) and vertical (cV) are provided from resize matrix with 200×180. The size of each of the coefficient matrix is 100×90. The column-wise standard deviation (stdcol) and row-wise standard deviation (stdrow) are attained from the four wavelet coefficients with size 1×180 and 1×200 respectively. The db10 wavelet feature vector is formed using these standard deviations with a size of 1×380 for one input image and initialize the training feature matrix (X) with a size of 800×380. After that, the mean and covariance matrix are calculated from the feature vector to find the eigenvalues and corresponding eigenvectors to reduce the feature space. Finally, the greatest 70 eigenvalues are selected as the most significant features from the eigenspace to build the transformed feature matrix (T) with a size of 800×70 .

Table 1: Experimental Information for Training Images

Serial No.	Feature	Value
1	No. of subject (person)	50
2	No. of images	1000
3	No. of training images	80%
4	No. of testing images	20%
5	Resize Images with dimension height×width (M×N)	200×180 Pixel
6	Wavelet coefficients cA cD cH cV	 100×90 double 100×90 double 100×90 double 100×90 double
7	The standard deviation of Wavelet coefficients Colum-wise (stdcol) Row-wise (stdrow)	 1×180 double 1×200 double
8	Wavelet feature vector (fvstd)	1×380 double
9	Mean of all feature vectors (*m*)	1×380 double
10	Initialize the training feature matrix (X)	800×380 double
11	Eigenvalues	70
12	Covariance matrix	380×380 double
13	Reduced transformation matrix P_{PCA}	380×70 double
14	Reduced feature vector fv_{PCA}	1×70 double
15	PCA transform dataset matrix (T)	800×70 double

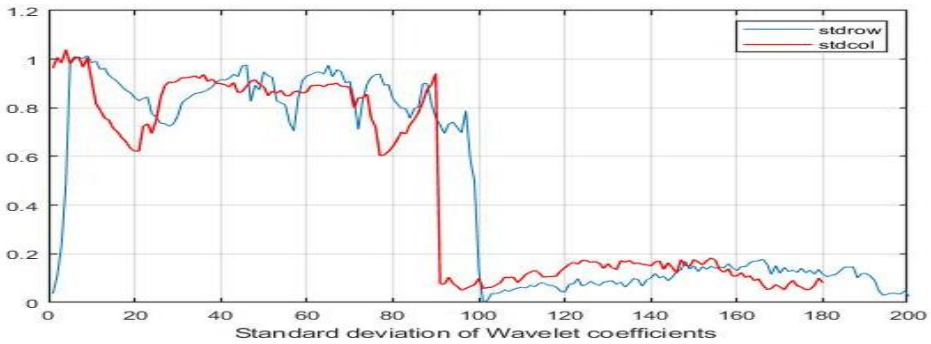


Figure 6: Standard deviation of wavelet coefficients for column-wise (stdcol) and row-wise (stdrow)

The calculated row-wise and column-wise standard deviations are represented in Fig. 6. From this figure, it can be observed that the row-wise standard deviation which captures variations in pixel intensity horizontally, whereas, the column-wise standard deviation captures the variations in pixel intensity vertically. It shows the most prominent feature of the feature vector. After combination of these two standard deviations, it can be obtained a db10 wavelet feature vector for a single training image with a size of 1 × 380 which is visualized in Fig. 7.

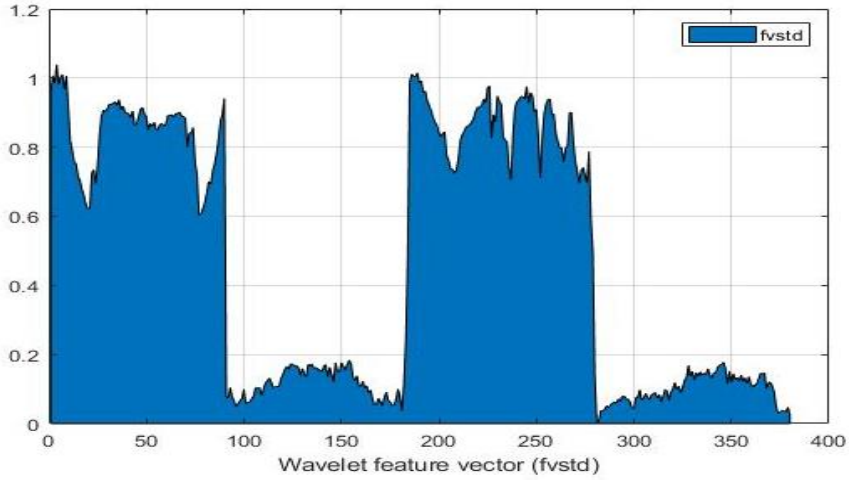


Figure 7: Wavelet feature vector extraction (fvstd)

In fact, Fig. 7 is a local spatial characteristics of each pixel value for the input images highlighted as a training feature vector which is a new representation by combining row-wise std and column-wise standard deviations. It can be observed from Fig. 7 that the pixel intensity both horizontally and vertically has a significant variation. After the formation of the wavelet feature vector, the training feature matrix is initialized as the standard form of size 800 × 380 which is pictured in Fig. 8 as the histogram form. It can be shown from Fig. 8 that the frequency level of the initialized training feature matrix (X) is around 14000 and the intensity value is highly dense in [-0.4, 0.4].

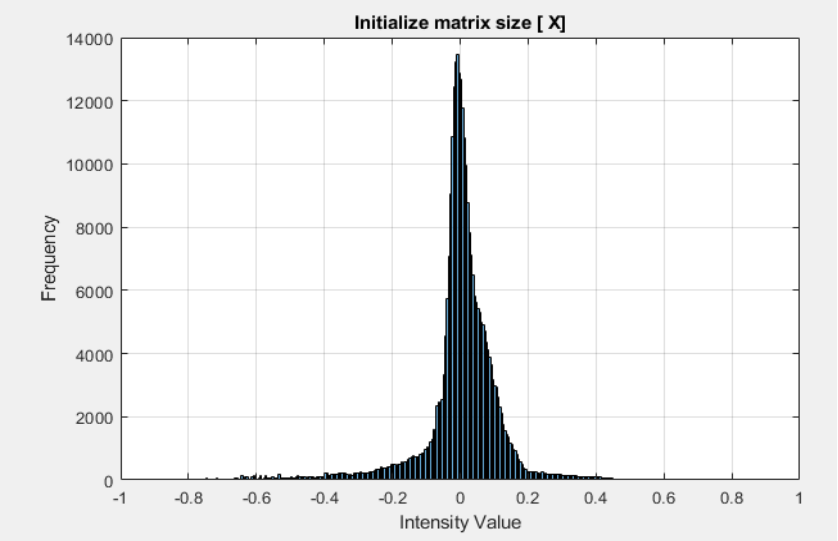


Figure 8: Histogram of initialize training feature matrix (X)

For avoiding the computational complexity, it has to reduce the feature dimension for training the classification model. The initialize training feature matrix (X) is transformed to PCA generated matrix (T) with size of 800×70 for 70 significant values. The PCA transformed feature matrix is visualized in Fig. 9 as the histogram form. The frequency level of transformed feature matrix is around 10000 but feature intensity is dense in same range which can be observed from Fig. 9.

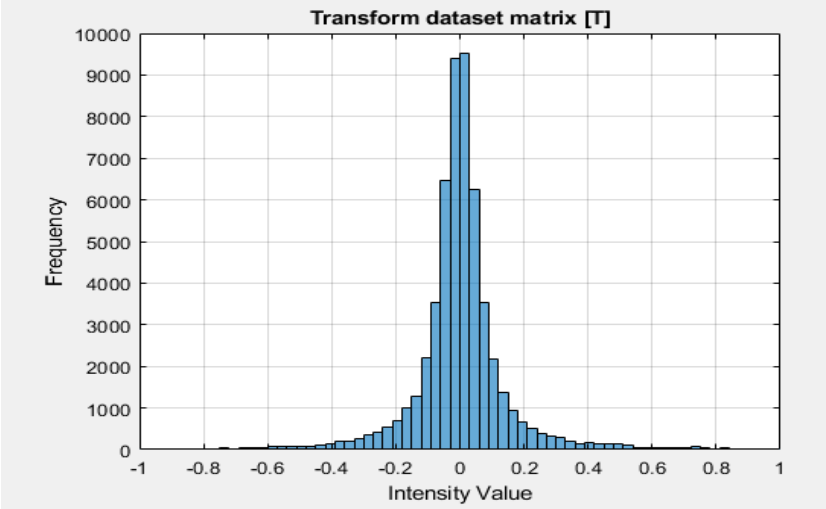


Figure 9: Histogram of transform data matrix (T) for training phase

After building the training model for face recognition, we have evaluated the model by 20% test images in the same protocol. The L_1 distance is calculated between each single test image and the training images. The nearest distance is considered as first match and second nearest value is second match and so on. First five matches are considered for a single test image and anticipated result has been obtained. Finally, 95% classification accuracy is obtained from the

confusion matrix for all the test images. The formulas for calculating accuracy, shown in equations 32 respectively [23,24].

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{32}$$

Evaluation Metrics Accuracy is the total number of correct predictions divided by the total number of predictions generated for the data set.

True Label

Predicted Label	Normal	Happy	Joy	Surprise	Screaming
Normal	38	0	1	1	0
Happy	1	38	1	0	0
Joy	0	1	37	0	2
Surprise	1	0	0	39	0
Screaming	0	1	1	0	38

Figure 10: Confusion Matrix for calculating accuracy

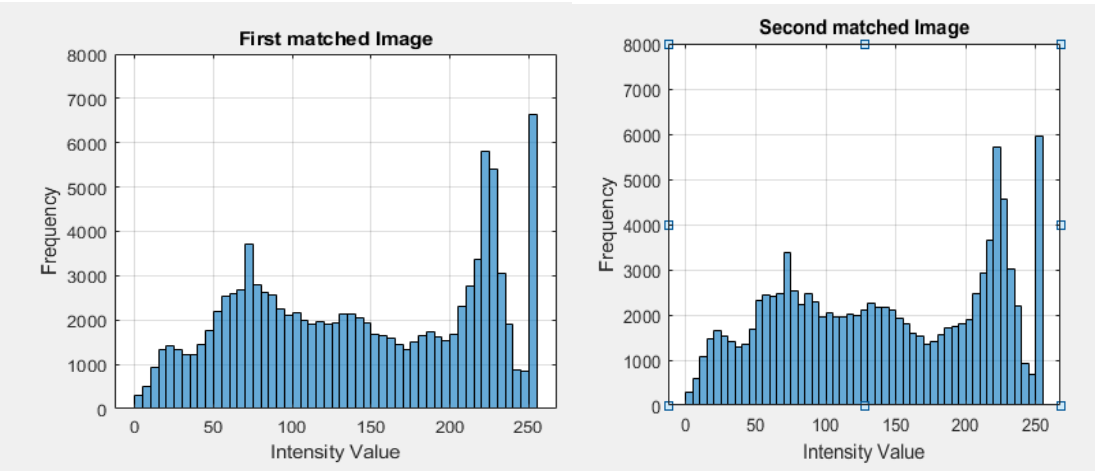
Table 2: Results analysis for testing image 801.jpg

Serial No.	Feature	Value
1	The reduced feature vector for this testing image (figure:10)	1×70 double
2	Wavelet feature vector (fvstd)	1×380 double
3	filename	'801.jpg'
4	flag	1x1000 double
5	Binarize (Ibin)	200x180 logical
6	index	800x1 double
7	Transform dataset	800x70 double
8	Result	800x1 double
9	Finding L_1 distance First nearest matched Second nearest matched Third nearest matched Four nearest matched Five nearest matched	 6.3103 7.48 8.13 8.59 8.96
10	% Average accuracy for all images is	95%

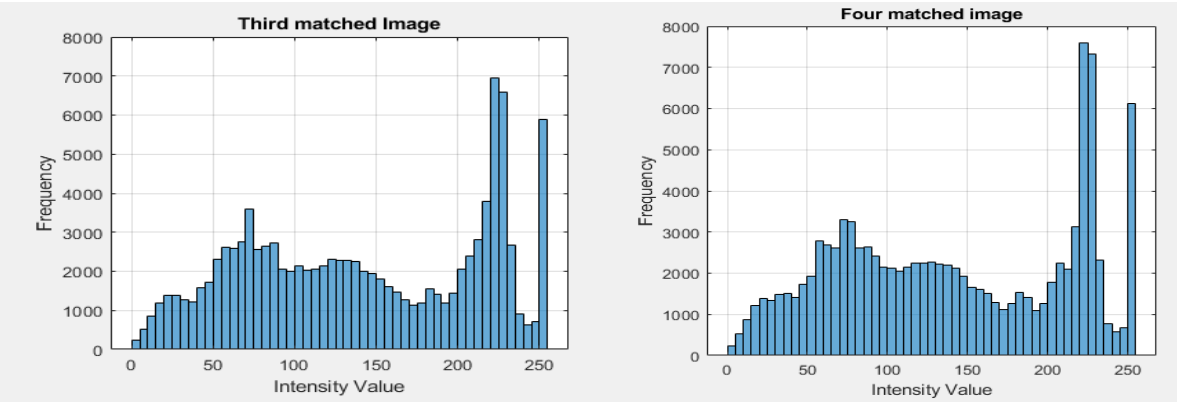


Figure 11: Test image and recognized image from the training faces.

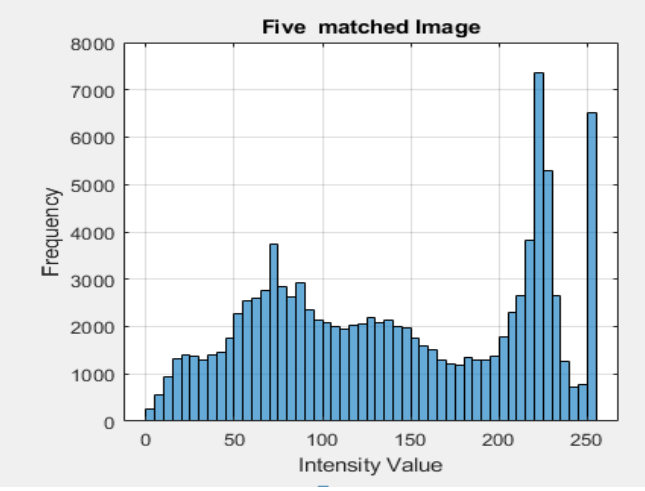
We have calculated the distance of the test image for each image from the training database. The minimum distance shows which image from the database matches the test image best. It is a sequential match compared with the first, second, third, and so on images. We are getting the similarity based on the finding of L1 distance. The best match is where we get the least distance between input images and the database (Figure 11).



(a) **(b)**



(c) **(d)**



(e)

Figure 12: Histogram to visualize this Result. (a) First nearest matched, (b) Second nearest matched (c) Third nearest matched, (d) Four nearest matched, (e) Five nearest matched

The above histogram visualizes the result for better understanding. It performs a sequential match with the first, second, third images and so on. The L_1 distance indicates the similarity with the images of the dataset. The best match is the one where the distance is least Figure 12.

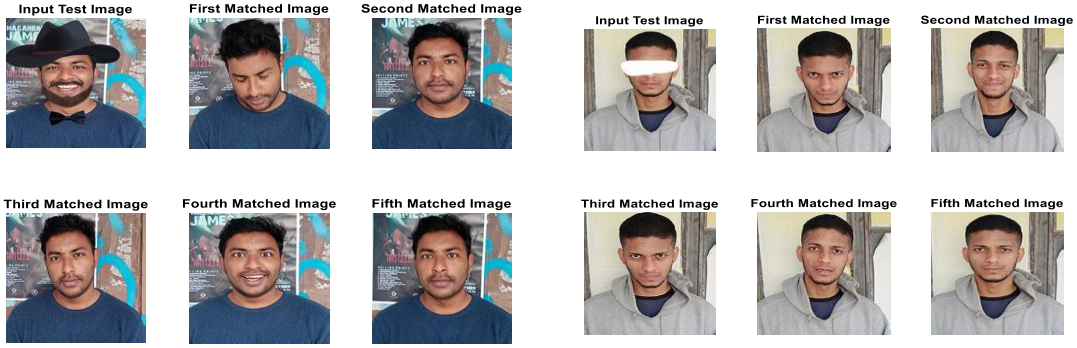


Figure 13: Distortion test image and recognized image from the training images.

If there is distortion in the test image, this technique also recognizes the image appropriately. In real life, suppose some person has given his face data with a clean shave, and after some days, he comes with a mustache and beard or some lady does heavy makeup or puts goggles on her face, it adds some noise and distorts this background and heavily distorting face. By using this technique, recognizing their faces is also possible. In this case, we have an image scratched white and added an artificial mustache and hat on the front. In spite of these distortions, the wavelet-based technique is able to provide the correct recognition Figure 13.

Discussion

The analyzed technique of Eigenface Recognition is good for recognition but the accuracy level is not satisfactory. So, to enhance the result in terms of more accuracy we have applied wavelet feature. Then we have combined them both and our outcome is better in terms of accuracy. This face recognition technique through this algorithm has an accuracy of 90%-93% for the Eigen Vector-based Face Recognition system and 95% accuracy for the Wavelet-based Face Recognition system. It provides better accuracy as it takes the most significant eigenvalues. The reduced dataset in this process takes less memory in the device and is easy to store. The algorithm can identify images having distortion in a test image. It means if any person does heavy makeup, puts on goggles, adds some noise, distorts the background, heavily distorts their face with white scratches, and adds an artificial mustache and hat on the front. Despite distortion, correct recognition is obtained. In this study, our goal is to develop a security system by using the algorithms Eigen Vector-based Face Recognition system and Wavelet-based Face Recognition system. By using these two algorithms, we have reached our desired goal. Face recognition helps with surveillance and is the primary way terrorists and criminals are identified. Face detection includes better security, easy-to-fast integration, and automated identification. This method is reliable in improving the digital security system in different aspects. There are also some limitations in our work in terms of the dataset of images such as light, pose, or computer calculating time. These limitations may be overcome by the adoption of smoother and noise-free data and a more efficient and higher-performing computer. This recognition technique may also be performed with machine learning with the advancement of technology.

CONCLUSION

Security is essential in every sphere of life as well as in society. The proposed method can play a vital role in the security system. The analyzed methods have a satisfactory accuracy level and significance in security. We can impose these techniques to develop digital security systems, identity systems, document management, and access control. In this study, we have described the Eigen Vector-based Face Recognition system and Wavelet-based Face Recognition system. Wavelet-PCA feature extraction is rapid and highly accurate in terms of recognition rate. Additionally, it offers minimal dimensionality for replicating and contrasting the outcomes. These are practical steps for developing a security system. The process is efficient and appropriate for real-time use. Both in terms of accuracy and processing speed, different runs of the face database and distortion image. The face recognition system has demonstrated better (95%) accuracy in several runs with the face dataset using Wavelet-based recognition than Eigenvector-based recognition. There are some limitations to this work as we have faced challenges with light, expression, and quality of images. If these challenges are overcome in

further work, the accuracy level may improve. The better accuracy may be helpful for future implementation related to face recognition.

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