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Original Article

Face Recognition Based on Windowing Techniques, with Compressed Hybrid Domain Features

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Abstract *- Face Recognition is used in human-machine interfaces for day-to-day activities in real-time applications. This paper proposes Face Recognition based on windowing techniques with compressed hybrid domain features. The face images are resized to 224x160 and are segmented into windows of sizes 4 x 4, 8 x 8, and 16 x 16. The hybrid features are extracted using Discrete Wavelet Transform (DWT) and the covariance concept on each window. The average covariance of each window is computed to obtain compressed final features. Artificial Neural Network (ANN) is used for classification to identify a person effectively. The obtained results of average recognition are around 98% for four benchmarked public face databases. It is observed that the proposed model attains a higher recognition rate with a reduced number of features compared with the existing methods.*

Keywords *- ANN, Biometrics, Covariance, DWT, Face Recognition.*

1. Introduction

Biometrics have been proven to provide distinct and reliable advantages over conventional techniques, such as PINs, tokens, or passwords that are easily forgotten and a person's documents that can be stolen or lost. Biometric traits are attributes based on a person's physical or behavioural features. Human biometric recognition is the science of determining a person's identity based on physical characteristics and behavioural patterns [1]. The biometric traits cannot be lost because they are linked to a person's physical characteristics and behaviour [2].

Almost all apps require the biometric validation of a user to prevent transactions that are forgeries. The primary social unit in society is the human being, who is recognized by facial images. Facial recognition systems are essential for many uses and are in high demand since facial photographs are often taken without physical contact or the subject's awareness. Applications include border security, forensic labs, crime investigation, access supervision systems, data security, verifying and identifying people to grant them access to online accounts, authorizing payments, tracking and monitoring employee attendance, directing specific advertisements to specific consumers, and many more. The required fundamental properties of biometrics for greater accuracy and security in biometric verification/identification systems, biometric features must adhere to the following rules [3].

Universality : Each person must possess certain biometric features.

Uniqueness : Individuals' biometric attributes must effectively differ from one another.

Permanence : The properties of biometric traits must not change over time.

Collectability : Gathering and measuring biometric sample data must be simple.

Acceptability : Users of the biometric system must be willing to provide samples and ready to accept its use.

Circumvention : Biometric trait fraud must be stopped.

Face Recognition (FR), which has several advantages over other biometric modalities, has emerged during the past twenty years as one of the most widespread biometric applications for accurate people identification. However, according to the most recent state-of-the-art data, FR still needs improvements under difficult and harsh situations. This is due to the extensive facial picture alterations, including illumination, position, and facial expression. It is crucial to use representative facial characteristics using feature extraction methods to get over these difficulties.

Contributions : In this paper, the face images are resized and segmented into 4 x 4, 8 x 8, and 16 x 16 windows. The transform domain DWT is applied on each window and considers only LL band coefficients. The covariance concept is used on LL band coefficient matrices, and finally, each matrix's average covariance is computed to obtain compressed final features. The acquired characteristics are classified using ANN for human recognition.

The rest of the paper is organized as follows: section 2 provides interrelated works of this paper, section 3 provides the proposed method details, section 4 provides results analysis, and Section 5 concludes the entire research.

2. Literature Survey

This section describes the existing research techniques presented by various authors on Face Recognition. Wang [4] proposed a novel method named fusion of Global and Local Structure (GLSF) from the feature taken from Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) into Locality Preserving Projection (LPP), considering both the global and the local structures. PCA and LDA are extraction methods based on the worldwide structure features. LPP and Orthogonal Laplacian Faces (OLF) methods are based on the local structure features.

Vikash and Rajesh Parihar [5] presented a technique based on eliminating and approximating distortion present in the altered images by evaluating between DFT and Wavelet-based image alteration methods. The comparison was made between DFT-based JPEG and Wavelets-based JPEG techniques on the Modification Ratio, Image Quality, MSE PSNR, etc. The distortion present in the image cannot be neglected during visual data acquisition, processing, and transmission and is exhibited as the random variation of brightness or colour in pictures and should be removed for image quality assessment, restoration, and enhancement.

Govardhan Mattela and Sandeep K. Gupta [6] proposed a facial authentication system from video streaming with light invariant using Gabor-mean-DWT. Here, the Gabor filter is used to obtain edges and texture features due to the limitations of massive measurement and high redundancy. The average-DWT feature reduction procedure decreases this limitation.

A technique using DWT and HOG for convolution-based feature extraction. The DWT obtains a compressed number of transform domain LL band coefficients. The HOG is used to find oriented gradients by comparing the LL band and coefficients. Finally, features are obtained by convolving LL with HOG coefficients.

Kumar et al. [7] proposed DWT, median filters and Savitzky-Golay Filter (SGF) to eradicate distortion. The extended dataset Cohn-Kanade (CK+) decomposes by many noises with changing elevations.

Meade et al. [8] compared the Face Recognition efficiency of Discrete Wavelet Transform (DWT), Principal Component Analysis (PCA) and Gabor Wavelets (GW). The PCA provides the best recognition performance by constructing an orthonormal to obtain the important facial features. The GW is used here to filter spatial-frequency features of the image at critical points of the face. The DWT is used in facial feature extraction and is functional for rotated types of facial appearance; this increases directional filtering capability.

Maafiri et al. [9] presented a feature extraction method for robust FR called Local binary pattern and Wavelet Kernel PCA (LWKPCA). The strategy aims to extract discriminant and powerful information to minimize recognition errors. This is obtained first by using a nonlinear projection algorithm called RKPCA. Then, the algorithm to reduce the dimensionality of features extracted using the proposed color local binary pattern and wavelets transformation called color LBP and wavelet descriptor. The general idea of our descriptor is to find the best representation of a face image in a discriminant vector structure by a novel feature grouping strategy generated by the three-level decomposition of Discrete Wavelet Transform (DWT) and Local Binary Pattern (LBP).

Yassin Kortli et al. [10] reviewed essential techniques approaches and provided the classification of their types. The advantages and disadvantages of different techniques are compared with robustness, complexity, accuracy and discrimination. Also discussed are the most commonly used databases, supervised and unsupervised learning types, results of the most frequently used techniques and challenges faced in handling these techniques.

Fahima Tabassum et al. [11] presented the coherence of Discrete Wavelet Transform (DWT) as joined with four different algorithms: error vector of Principal Component Analysis (PCA), eigenvector of PCA, eigenvector of Linear Discriminant Analysis (LDA) and Convolutional Neural Network (CNN) then a combination of four results are done using the entropy of detection probability and Fuzzy system.

Kak et al. [12] proposed the Convolution Neural Network (CNN) architecture used in the extracting phase of significant features of the face shape and the SoftMax classification layer to identify faces in the fully connected CNN layer. This provides an updated CNN architecture by applying a three-batch normalization layer to the CNN design. Using this modification increased the system network speed with a better recognition rate. The recognition rate also increased by applying two DWT levels with a bio5.5 filter to the training group of the database images and the tested image before applying the PCA dimensional reduction algorithm instead of using the PCA algorithm alone.

Wang and Wu [13] introduced a Face Recognition method based on PCA and SVM. Finally, this method is used to recognize the Labelled Faces in the Wild (LFW) face data set, and the parameter adjuster named grid search cv is used to adjust the parameters further to improve the precision and recall of Face Recognition. The experimental results show that the Face Recognition technology based on PCA and SVM reduces the dimension of face data and increases the recognition accuracy, which is a feasible Face Recognition method.

Lin and Linares Otoya [14] proposed a pose-invariant Face Recognition framework based on significant pose detection and facial landmark description. During the training phase, a large pose detector model is proposed to process the 2D spatial distributions of the detected facial landmarks on face images. This model can notice whether the yaw angle of the face is large or small (semi-frontal face image).

This results in two face pose scenarios. Then, a feature descriptor is applied to a set of predefined facial landmarks on a face image to obtain the feature vectors. These feature vectors train two Face Recognition models for each person in the database. One for the large pose scenario and the other for the semi-frontal pose scenario. During the testing phase, the large pose detector selects a type of Face Recognition model (large or semi-frontal). The chosen model is utilized to determine the identity of the person. In this study, the CMU-PIE database is employed.

Three feature descriptors, SIFT, HOG, and LBP, are adopted for comparison. The models used for Face Recognition are SVM, GMM, and Naive Bayes. The novelty of the proposed method is using a large pose detector to improve the Face Recognition rate.

Cevik [15] presented Hexagonal pixel-based Image Processing (HIP) versions of the most basic texture extraction studies in Square pixel-based Image Processing (SIP), namely Gray-Level-Co-occurrence-Matrices (GLCM), Local Binary Pattern (LBP), and their work, Local-Holistic Graph-based Descriptor (LHGPD). The images are first transformed from the SIP domain to the HIP domain. The HIP domain equivalences (HexGLCM, HexLBP, and HexLHGPD) of the SIP domain GLCM, LBP, and LHGPD are then established. Finally, the facial recognition performances of the SIP and HIP domain versions of GLCM, LBP, and LHGPD are evaluated and compared on the primary data sets.

Lan et al. [16] proposed an Alternating Training Framework (ATF), which influences the resemblance and diversity across multiple datasets to obtain a robust face detector. ATF contains two sub-modules: Alternating Training with Decreasing Proportions (ATDP) and Mixed Branch Loss (MBL).

The ATDP trains numerous datasets simultaneously via a weakly supervised way to take benefit of their diversity, and MBL utilizes similar landmark pairs to constrain different branches of the corresponding datasets. Besides, they extend the framework to handle three situations easily: single target detector, joint detector, and novel detector.

Karanwal [17] suggested that Neighborhood Difference LBP (ND-LBP) and Neighborhood Mean LBP (NM-LBP) were proposed as two LBP versions (NM-LBP). In ND-LBP, the comparison is made between neighbour pixels lined up clockwise, whereas, in NM-LBP, the neighbours are compared with their mean. The face descriptor ND-LBP+NM-LBP is constructed by combining the histograms of ND-LBP and NM-LBP. The PCA idea is for compression, and the SVMs and NN classifiers are utilized for Face Recognition.

Atamuradov et al. [18] investigated the efficiency of the proposed system by including additive white Gaussian noise in the test images in the face dataset. The two algorithms are DWT and Dual-Tree Complex Wavelets Transform (DTCWT) are used for denoising. The de-noised ideas are then nurtured with PCA-based Face Recognition for improved results.

Rifha Ilyas Bendjillali et al. [19] proposed a facial expressions identification system using the Viola-Jones algorithm to detect the faces from the image and enhance the face image by histogram equalization. This used DWT to extract the features, then fed to a Convolutional Neural Network (CNN) classifier.

Taif Alobaidi and Wasfy B. Mikhael [20] presented a Face Recognition system based on fused feature extraction domains. The DWT technique is utilized here on face images to obtain initial features and also applied DCT to get the final features. The ED matching method calculates the minimum matching distance between the training matrix and the testing image. Monisha et al. [21] proposed facial identification based on 2D-DWT feature extraction and a Qualified Significant Wavelet Tree to get the correct yield while compressing the face images. The Convolution Neural Network (CNN) is used for classification.

Kourosh Kiani and Sepideh Rezaeirad [22] proposed a facial recognition system on half of the face image using DWT to generate the reflection vectors and hidden markov model classifier. This system is used to manipulate the axis-symmetrical stuff to Face Recognition using half of the face to spread the statistical-based models. The computational time and complexity of the model are reduced by using half of the input image instead of the entire image to recognize the persons.

Alobaidi and Mikhael [23] presented a sparse depiction method for Face Recognition through the ℓ 2 rule. The features of two non-orthogonal approaches, DCT and DWT, are used independently or fused to get face identification schemes. A fused SRFI scheme is weight-based designated factors from the DCT and DWT fields. Nibble-based Face Recognition using the convolution of hybrid features for Face Recognition. Here, the authors proposed left-side and right-side nibble bits for fast computational speed for Face Recognition. In Summary, for face frontalization, GAN-based approaches provide the best performance for frontal face generation and recognition under huge pose variations and expressions.

Lahaw et al. [24] exploited the idea of 2D-DWT for image compression as a preprocessing in Face Recognition. The DWT is executed at different scales and placements for sensitivity to varying lighting conditions and facial details. The LL sub-band of the processed image is used for the feature extraction with ICA, PCA, LDA, and SVM algorithms.

Sumathi and Christopher Derairaj [25] proposed the Face Recognition of occlusion, pose, and illumination variations. The Principal Component Analysis and DWT are applied to extract the features, and SVM is used for classification [26, 27]. Fahima Tabassum et al. [28] proposed a system to improve the percentage accuracy of object recognition using a combination of DWT with four other feature extraction techniques viz., Principal Component Analysis (PCA) error vector, PCA eigenvector, an eigenvector of Linear Discriminant Analysis, and Convolutional Neural Network [29]. The four outcomes are combined using probability detection entropy and a fuzzy system. The result of this proposal discloses better results compared to previous works.

3. Proposed Model

The Face Recognition model is developed using the window technique by segmenting face images with different sizes. The DWT is utilized on each window and considers only the LL band matrix as the initial feature. The covariance of the LL band matrix is computed, and an average of each matrix gives the final feature value. The block diagram of the proposed model is shown in Figure 1.

3.1. Face Image Databases

The standard face databases, viz., Olivetti Research Laboratory (ORL), Japanese Female Facial Expression (JAFFE), Yale, and Extended Yale B (EYB), are used to examine the performance of the proposed method.

3.1.1. Olivetti Research Laboratory (ORL) Face Data Base [30]

The database, which contains 400 photos for 40 people and 10 photographs per person, is commonly utilized in facial recognition research. With every image size of 112X92 in grayscale format, the face photographs feature a variety of poses and facial emotions. The ORL dataset sample face photos of six people are shown in Figure 2.

3.1.2. The Japanese Female Facial Expressions (JAFFE) [31]

The dataset, which consisted of 213 face images with 256X256 grayscale facial photos taken from ten people, was published in 1998. They included pictures with facial appearances such as neutral, fear, shock, happiness, dissatisfaction, wrath, and contempt. The sample face photos of six people from the JAFFE dataset are shown in Figure 3.

3.1.3. Yale Face Database [32]

Yale University provided the dataset in 1997, including 165 photos of 15 people, each with eleven facial appearances and illumination images. Every face image is 243X320 grayscale pixels in size. The facial image samples of six people from the Yale database are shown in Figure 4.

3.1.4. Extended Yale B Face Database [33]

The dataset contains 2414 frontal-face images with a size of 192x168 over 38 subjects and about 64 images per subject. The images were captured under different lighting conditions and various facial expressions. All the photos are cropped and resized to 92 x 168. The 64 samples were divided into five subsets depending on the face angle and light direction [34]. Image samples of the cropped EYB dataset are shown in Figure 5.

3.2. Feature Extraction

Preprocessing and feature extraction is the most vibrant part of human identification. The following subdivisions provide an effective proposed feature extraction technique for face identification.

3.2.1. Windowing Technique

The face images from the four benchmark face databases are considered for result analysis. The face database images are resized to an image size of 224 x 160. The whole face image is segmented into sizes 4 x 4, 8 x 8, and 16 x 16, corresponding to 16, 64, and 256 windows, as shown in Figure 6. Each cell in 4 x 4, 8 x 8, and 16 x 16 windows are of sizes 56 x 40, 28 x 20, and 14 x 10, respectively.

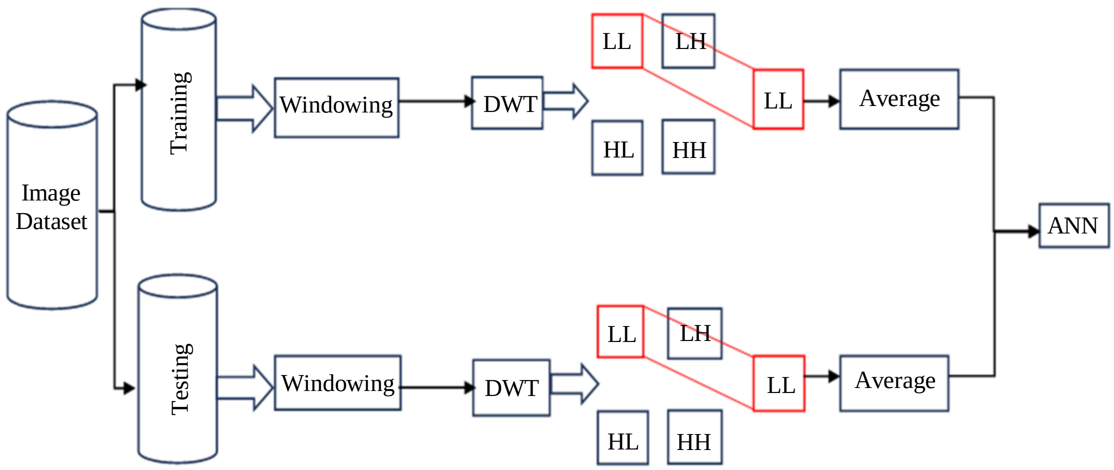

Fig. 1 The proposed model

Fig. 2 Samples of face images from six ORL dataset persons [30]

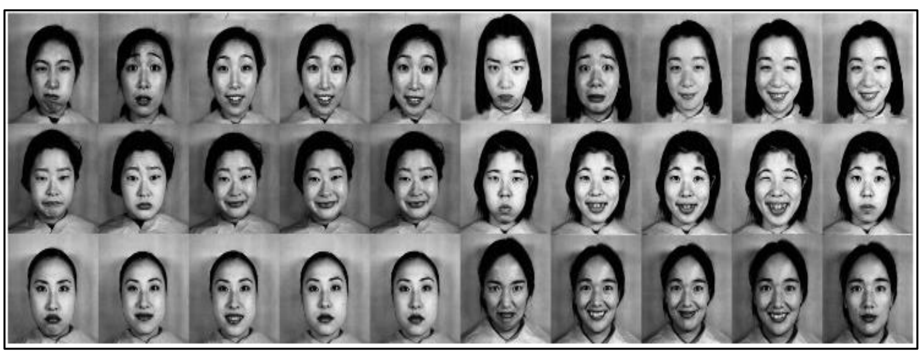

Fig. 3 The JAFFE dataset samples six subjects [31]

Fig. 4 The Yale face image dataset sample of six persons of [32]

Fig. 5 Face image samples of extended Yale B Face database [33]

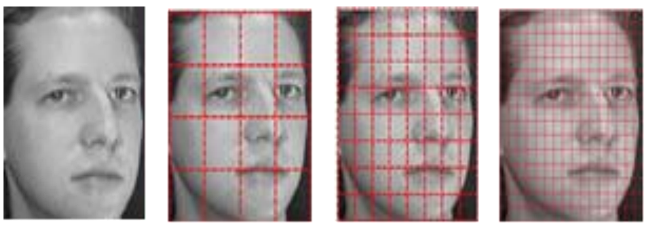

Fig. 6 Windowing technique: original image, 4 x 4, 8 x 8, and 16 x 16 window segments

3.2.2. Discrete Wavelet Transform (DWT) on Each Cell of the Window

It is a powerful tool to convert spatial domain images into frequency domain consisting of low and high-frequency coefficients using Low and High Pass Filters with decimation by 2. The DWT is applied on the window of an image to obtain low and high-frequency coefficient bands. The frequency domain has four rounds of equal size, corresponding to three high-frequency bands and one low-frequency band. The essential data of the original face image is present in the low-frequency band. The insignificant edge data of the original face image exists in three high-frequency bands corresponding to horizontal, vertical, and diagonal edges. In our method, the low-frequency band coefficients are considered by omitting high-frequency band coefficients as features for Face Recognition, resulting in low dimensional final parts for high-speed computation. The coefficients of the low-frequency band Low-Low (LL), and high-frequency bands viz., Low-High (LH), High-Low (HL), and High-High (HH) are acquired based on equations 1- 5 for the image matrix of size 2X2.

$$X = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \tag{1}$$

$$LL = \frac{a+b+c+d}{2} \tag{2}$$

$$LH = \frac{a+b-c-d}{2} \tag{3}$$

$$HL = \frac{a-b+c-d}{2} \tag{4}$$

$$HH = \frac{a-b-c+d}{2} \tag{5}$$

Where a, b, c and d are the coefficients of the 2X2 matrix. DWT is applied on each window cell of 4 x 4, 8 x 8, and 16 x 16 windows of sizes 56 x 40, 28 x 20, and 14 x 10, respectively, to obtain the corresponding resultant four DWT bands of LL, LH, HL, and HH coefficients. Finally, only the LL band matrix is considered for further processing, consisting of compressed, significant, and noiseless information. The LL band dimensions of each window cell of 4 x 4, 8 x 8, and 16 x 16 are 28x20, 14x10, and 7x5, respectively.

3.2.3. Computation of Covariance on the LL Band Coefficients

It is a statistical tool used to determine the relationship between the movements of two random variables. It is used for computing the covariance between every data matrix column. The covariance matrix is always a square of size equal to the number of columns. Covariance measures the variations of two variables that are related.

3.2.4. Illustration of covariance computation [35]

Consider a matrix of size $5x3$,

$$\begin{array}{cc} & \begin{array}{ccc} X & Y & Z \end{array} \\ A = & \begin{bmatrix} 64 & 580 & 29 \\ 66 & 570 & 33 \\ 68 & 590 & 37 \\ 69 & 660 & 46 \\ 73 & 600 & 55 \end{bmatrix} \end{array}$$

The covariance matrix of A is given in matrix B of size 3x3,

$$\begin{array}{cc} & \begin{array}{ccc} X & Y & Z \end{array} \\ = & \begin{bmatrix} \mathrm{cov}(X,X) & \mathrm{cov}(X,X) & \mathrm{cov}(X,X) \\ \mathrm{cov}(X,X) & \mathrm{cov}(X,X) & \mathrm{cov}(X,X) \\ \mathrm{cov}(X,X) & \mathrm{cov}(X,X) & \mathrm{cov}(X,X) \end{bmatrix} \end{array}$$

$$\mathrm{Cov}(X,X) = \mathrm{Var}(X) = \frac{1}{(n-1)}\sum_{i=0}^{n}(X_i - \bar{X})^2$$

$$\mathrm{Cov}(Y,Y) = \mathrm{Var}(Y) = \frac{1}{(n-1)}\sum_{i=0}^{n}(Y_i - \bar{Y})^2$$

$$\mathrm{Cov}(Z,Z) = \mathrm{Var}(Z) = \frac{1}{(n-1)}\sum_{i=0}^{n}(Z_i - \bar{Z})^2$$

$$\mathrm{Cov}(X,Y) = \frac{1}{(n-1)}\sum_{i=0}^{n}(X_i - \bar{X})(X_i - \bar{X}) = \mathrm{Cov}(Y,X)$$

$$\mathrm{Cov}(X,Z) = \frac{1}{(n-1)}\sum_{i=0}^{n}(X_i - \bar{X})(Z_i - \bar{Z}) = \mathrm{Cov}(Z,X)$$

$$\mathrm{Cov}(Y,Z) = \frac{1}{(n-1)}\sum_{i=0}^{n}(Y_i - \bar{Y})(Z_i - \bar{Z}) = \mathrm{Cov}(Z,Y)$$

Covariance is computed on the Matrix.

$$A = B = \begin{bmatrix} 11.5 & 50 & 34.75 \\ 50 & 1250 & 205 \\ 34.75 & 205 & 110 \end{bmatrix}$$

Where, n = Number of elements in column
$\overline{X}$, $\overline{Y}$ and $\overline{Z}$ = Mean of X, Y, and Z
Cov = Covariance
Var = Variance
$\overline{X}$ = 68, $\overline{Y}$ = 600, $\overline{Z}$ = 40, n = 5

The covariance of each LL band dimensions 28 X 20 of window cells of 4 X 4 is computed. The resultant covariance matrix is of size 20 X 20 square matrix. The total number of cells available is sixteen, with dimensions 20 X 20. The covariance of each LL band dimension 14 X10 of window cells 8 X 8 is computed. The resultant covariance matrix is of size 10 X 10 square matrix. The total number of cells available is sixty-four with dimensions 10 X 10. The covariance of each LL band measurements 7 X 5 of window cells of 16 X 16 is computed. The resultant covariance matrix is of size 5 X 5 square matrix. The total number of cells available is two hundred fifty-six with dimensions 5 X 5.

3.2.5. Average Covariance Matrix of LL Band

The average value of each covariance matrix is computed for 4 X 4, 8 X 8 and 16 X 16 window segments, resulting in a single value for every window. The dimensions of the average covariance matrix are 4 X 4, 8 X 8 and 16 X 16 for the original image size of 224 x 160. The intermediate Covance matrix is converted into a column vector with 16, 64 and 256 coefficients for window cells of 4 X 4, 8 X 8 and 16 X 16. The final number of features is compressed and practical. The initial size of an image is 224 X 160 =35840 pixels, and are reduced to 16, 64, and 256 for window cells of 4 X 4, 8 X 8 and 16 X 16, respectively.

3.3. Classification Using Artificial Neural Networks (ANN)

It is formed as a base of Deep Learning and a subset of Machine Learning where the model is similar to the construction of the human brain. It consists of many layers with nodes called artificial neurons. These neurons receive signals and then process them to transmit them to another node of the other layer. Neurons and connections between layers have a weight that adjusts as learning proceeds, and weight increases or decreases the strength of the signal at connections [36]. ANN is composed of three fundamental layers. The first layer is the input layer, which receives the features as input. In between exist the hidden layers, which perform most of the computation required by the network; the final layer is the output layer, which anticipates the ultimate output. The structure of ANN is shown in Figure 7.

The training of an ANN is conducted by determining the difference between the processed predicted output of the network and the target output that leads to the error. The network then adjusts its weighted associations according to a learning rule and uses this error value. Successive adjustments cause the ANN to produce an increasingly similar predicted output to the target output.

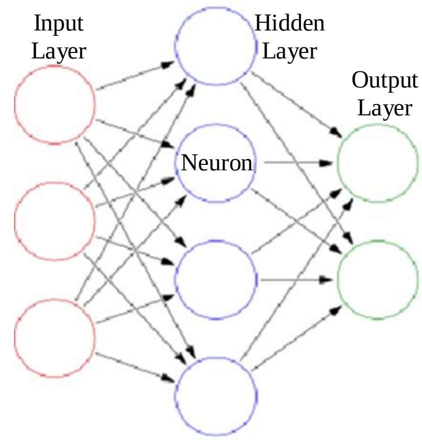

Fig. 7 ANN structure

After a sufficient number of these adjustments, the training can be terminated based on specific criteria. This is a form of supervised learning.ANN has found applications in many disciplines because of its ability to reproduce and model nonlinear processes. Application areas include system identification and control quantum chemistry, general game playing, pattern recognition like radar systems, face identification, signal classification, 3D reconstruction, object recognition and more, sensor data analysis, sequence recognition like gesture, speech, handwritten and printed text recognition, medical diagnosis, finance, e.g. ex-ante models for specific financial long-run forecasts and artificial financial markets, data mining, visualization, machine translation, social network filtering, and e-mail spam filtering.

The features obtained from the proposed method are fed as input to the ANN. The final features obtained from the face dataset are 16, 64, and 256 for 4 x 4, 8 x 8, and 16 x 16 windows, respectively. The pattern recognition network uses the hidden layers, transfer, and error functions. The network is trained continuously for several epochs. The network output is compared with the target data during training, and an appropriate error is produced. The obtained error is fed back to the hidden layer for updating the weights and trained to get the desired output values. The network is tested against new data to assess network performance. If the network's performance is not good, then the network is trained again or increases the number of neurons.

4. Performance Result Analysis

The proposed windowing approach with DWT and average covariance, the experiments are executed on four well-known face databases to assess the efficiency of the planned model. All the facial image sizes are resized to 224 x 160 in the dataset and are segmented into 4 x 4, 8 x 8, and 16 x 16 dimensions using the windowing technique. The number of images in the database is divided into training and testing in the various ratios. Twenty-five hidden nodes are considered for all the experiments. The experiment aimed to evaluate through supervised learning how the increase in the windowing size and number of trained images affects the recognition precision, given that the hidden nodes remain constant. The performance parameters, such as percentage recognition and total error rates, are computed to verify the proposed model's efficiency.

4.1. Result Analysis on ORL Database

The ORL database comprises 400 face images split arbitrarily into the training and test dataset ratio. The training and test ratios combination are 10:90, 30:70, 50:50, 70:30, and 90:10, considered to test the proposed model as given in Table 1. The final features obtained from the ORL face dataset 16, 64, and 256 for 4 X 4, 8 X 8, and 16 X 16 windows are input to the ANN. It is observed that the percentage recognition rate increases with an increase in the number of images for training; however, the percentage total error decreases with an increase in the number of images for training for all sizes of windows. The size of 16 X 16 gives better results than that of 8 X 8 and 4 X 4 as the number of features is sufficient to identify face images.

4.1.1. Comparison of Proposed Method with Existing Methods Using ORL Face Dataset

The recognition accuracies on the ORL dataset achieved using existing methods are compared with the proposed method, as shown in Table 2. The comparison indicates that the current techniques presented by Liu et al. [37] and Maafiri and Chougdali [38] exhibit lower recognition accuracy than the proposed method for all window sizes; hence, our approach is better.

4.2. Result Analysis on the JAFFE Dataset

The JAFFE database comprises 213 face images split arbitrarily into the training and test dataset ratio. The training and test ratios combination are 10:90, 30:70, 50:50, 70:30, and 90:10, considered to test the proposed model as given in Table 3. The final features obtained from the JAFFE face dataset 16, 64, and 256 for 4 x 4, 8 x 8, and 16 x 16 windows are fed as input to the ANN. It is observed that the percentage recognition rate increases with an increase in the number of images for training; however, the percentage total error decreases with an increase in the number of images for training for all sizes of windows. The window size of 16X16 gives better results compared to window sizes of 8X8 and 4X4 as the number of features is sufficient to identify face images. In this face dataset, the percentage recognition is 100, and the error is zero for training and testing ratio is more than 50:50 since the face image variations are very few.

4.2.1. Comparison of the Proposed Method with Existing Methods Using the JAFFE Face Dataset

The recognition accuracies on the JAFFE dataset achieved using existing methods are compared with the proposed method, as shown in Table 4. From the comparison, it is found that the current techniques presented by Refat and Azlan [39], Ozdemir et al. [40], and Wu et al. [41] exhibit lower recognition accuracy compared to the proposed method for all window sizes; hence our method is better. The accuracy values in the proposed way for all window sizes are 100%; however, these values decrease by increasing the number of images in the different databases.

Table 1. The performance measure using the ORL face image dataset

Window Size	Train: Test	10:90	30:70	50:50	70:30	90:10
4X4	Recognition Rate (%)	44.75	77.00	90.75	95.25	97.25
	TER (%)	0.1275	0.0319	0.0114	0.0045	0.0016
8X8	Recognition Rate (%)	48.75	85.00	91.75	97.25	97.55
	TER (%)	0.1052	0.0282	0.0070	0.0022	0.0013
16X16	Recognition Rate (%)	49.75	86.50	93.00	98.50	98.75
	TER (%)	0.0922	0.0267	0.0019	0.0016	0.0010

Table 2. Accuracy comparison of the proposed method with the existing techniques on the ORL dataset

Sl. No.	Authors and Year	Techniques	Accuracy (%)
1	Liu et al., [37], 2019	Transfer learning-based sparse representation and weighted fusion	95.00
2	Maafiri, and Chougdali [38], 2019	Wavelets feature extraction method in preprocessing and L1-Norm PCA	96.70
3	Proposed Method	4x4 window with DWT	97.25
		8x8 window with DWT	97.55
		16x16 window with DWT	98.75

Table 3. The performance measure using the JEFFE face image dataset

Window Size	Train: Test	10:90	30:70	50:50	70:30	90:10
4X4	Recognition Rate (%)	75.00	96.50	100.00	100.00	100.00
	TER (%)	0.1906	0.0389	0.0000	0.0000	0.0000
8X8	Recognition Rate (%)	76.00	97.50	100.00	100.00	100.00
	TER (%)	0.1864	0.0324	0.0002	0.0000	0.0000
16X16	Recognition Rate (%)	77.00	99.50	100.00	100.00	100.00
	TER (%)	0.179	0.0039	0.0000	0.0000	0.0000

Table 4. Recognition accuracy comparison of the proposed method with the existing methods using the JAFFE dataset

Sl. No.	Authors and Year	Techniques	Accuracy (%)
1	Refat and Azlan [39], 2019	Deep belief network and CNN	97.01
2	Ozdemir et al., [40], 2019	LeNet model with CNN	96.43
3	Wu et al., [41], 2019	GCN network with six graph convolutions	96.42
4	Proposed Method	4x4 window with DWT	100
		8x8 window with DWT	100
		16x16 window with DWT	100

4.3. Result Analysis on the Yale Dataset

The Yale database comprises 165 face images, which are split arbitrarily into the training and test dataset ratio. The training and test ratios combination are 10:90, 30:70, 50:50, 70:30, and 90:10, considered to test the proposed model as given in Table 5. The final features obtained from the Yale face dataset 16, 64, and 256 for 4 x 4, 8 x 8, and 16 x 16 windows are fed as input to the ANN. It is observed that the percentage recognition rate increases with an increase in the number of images for training; however, the percentage total error decreases with an increase in the number of images for training for all sizes of windows. The window size of 16X16 gives better results compared to window sizes of 8X8 and 4X4 as the number of features is sufficient to identify face images.

4.3.1. Comparison of the Proposed Method with Existing Methods Using the Yale Face Dataset

The recognition accuracies on the Yale dataset achieved using existing methods are compared with the proposed method, as shown in Table 6. From the comparison, it is found that the current methods presented by Alobaidi and Mikhael [42] and Wang and Qiao [43] exhibit lower recognition accuracy compared to the proposed method for all window sizes; hence our approach is better. The accuracy values in the proposed way for all window sizes are 99.66%; however, these values decrease by increasing the number of images in the different databases.

4.4. Result Analysis on Extended Yale Dataset

The Extended Yale database comprises 2414 face images split arbitrarily into the training and test dataset ratio. The training and test ratios combination are 10:90, 30:70, 50:50, 70:30, and 90:10, considered to test the proposed model as given in Table 7. The final features obtained from the Extended Yale face dataset 16, 64, and 256 for 4 x 4, 8 x 8, and 16 x 16 windows are fed as input to the ANN. It is observed that the percentage recognition rate increases with an increase in the number of images for training; however, the percentage total error decreases with an increase in the number of images for training for all sizes of windows. The window size of 16X16 gives better results compared to window sizes of 8X8 and 4X4 as the number of features is sufficient to identify face images.

Table 5. The performance measure using the Yale face image dataset

Window Size	Train: Test	10:90	30:70	50:50	70:30	90:10
4X4	Recognition Rate (%)	47.33	79.33	90.00	94.66	98.90
	TER (%)	0.3915	0.0922	0.0400	0.0290	0.0045
8X8	Recognition Rate (%)	48.00	84.00	90.66	95.66	99.33
	TER (%)	0.3022	0.0479	0.0277	0.0122	0.0037
16X16	Recognition Rate (%)	49.33	88.00	93.33	96.66	99.66
	TER (%)	0.2561	0.0380	0.0144	0.0072	0.0030

Table 6. Recognition accuracy comparison of the proposed method with the existing methods using the Yale dataset

Sl. No.	Authors and Year	Techniques	Accuracy (%)
1	Alobaidi, and Mikhael [42], 2019	DWT and DCT	98.89
2	Wang, and Qiao [43], 2019	LBP and DBN	97.79
3	Proposed Method	4x4 window with DWT	98.90
		8x8 window with DWT	99.33
		16x16 window with DWT	99.66

Table 7. The performance measure using the extended Yale face image dataset

Window Size	Train: Test	10:90	30:70	50:50	70:30	90:10
4X4	Recognition Rate (%)	39.48	62.77	70.51	70.06	72.58
	TER (%)	0.1199	0.0470	0.0368	0.0356	0.0329
8X8	Recognition Rate (%)	58.77	82.64	88.00	89.80	90.45
	TER (%)	0.0662	0.0227	0.0178	0.0155	0.0151
16X16	Recognition Rate (%)	64.32	86.64	91.61	93.35	94.00
	TER (%)	0.0531	0.0198	0.0157	0.0131	0.0132

Table 8. Recognition accuracy comparison of the proposed method with the existing methods using the extended Yale dataset

Sl. No.	Authors and Year	Techniques	Accuracy (%)
1	Hu et al., [44], 2020	Diagonal symmetric pattern pixels and pre-trained deep learning model	92.13
2	Zeng et al., [45], 2018	Combined traditional and deep convolutional neural network	88.30
3	Proposed Method	4x4 window with DWT	72.58
		8x8 window with DWT	90.45
		16x16 window with DWT	94.00

4.4.1. Comparison of Proposed Method with Existing Methods Using Extended Yale Face Dataset

The recognition accuracies on the Extended Yale dataset achieved using existing methods are compared with the proposed plan is shown in Table 8. The comparison indicates that the current methods presented by Hu et al. [44] and Zeng et al. [45] exhibit lower recognition accuracy than the proposed method for all window sizes; hence, our way is better.

The performance results indicate that the proposed method achieves a better recognition rate than the existing systems for the following reasons.

- The windowing approach is used to segment the whole image into 4 x 4, 8 x 8 and 16 x 16 window sizes. The DWT is applied to the segmented image. The covariance matrix is calculated, and the average on each covariance matrix is considered, resulting in fewer features 16, 64 and 256 for 4 x 4, 8 x 8 and 16 x 16 window sizes, respectively.
- Due to the fewer final features, the proposed method's processing time and computation complexity are much less.
- The performance of the proposed method is tested by varying the number of training images ratios.

5. Conclusion

Face Recognition has been proliferating over the past decade for almost all human-related applications like video surveillance, building access control, human identification, and autonomous vehicles are few examples of concrete. The paper proposes a novel Face Recognition based on windowing techniques with compressed hybrid domain features. The benchmarked publicly available face databases are resized to 224x160 and used to test the method's efficiency. All the face images are segmented into windows of sizes 4 x 4, 8 x 8 and 16 x 16.

The lesser number of LL band coefficients of DWT are obtained from each window after applying DWT. The covariance of each LL band matrix is calculated, and finally, the average covariance coefficient of every matrix is computed, resulting in 16, 64 and 256 features for window sizes of 4 x 4, 8 x 8 and 16x16, respectively. The obtained features are fed to the ANN to train and test the proposed model. The model with 16 x 16 window size results in a higher recognition rate compared to 4 x 4 and 8 x 8 window size with increased training samples. It is observed that the proposed method has a better recognition rate compared to existing methods.

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