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Automated Face Recognition System by PCA and DWT Feature Engineering with Optimized Machine Learning Methods

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Abstract The Principal Component Analysis (PCA) is a technique that reduces data dimension by synthesizing important representative features. Discrete Wavelet Transform (DWT) is a strong signal processing tool that can analyze the image in multi-resolutions and can discover significant features like edges. Properly trained supervised machine learning models can recognize input face pretty correctly. In this work face features extracted using PCA and DWT are assembled together to train various Machine Learning Models. Each model is studied using four benchmark face data sets namely YALE, JAFEE, GEORGIA TECH and ORL. The models are further optimized and their performances compared with existing state of the art methods. For YALE the proposed method achieved 94.54% accuracy using Logistic regression, for JAFEE 99.5% accuracy in Logistic regression, for GEORGIA TECH and ORL the method also out performs the existing techniques by achieving 84.6% and 98.5% accuracies.

Keywords-- Face recognition, PCA, DWT, KNN, Logistic Regression, SVM, Random Forest

I. INTRODUCTION

Face recognition system is a biometric authentication system that has replaced the traditional authentication systems like username, password, OTP (One Time Password), ID card etc. [1, 2, 3, 4]. The traditional systems depends on individual memory which can be easily forgotten or stolen. As a result the identity can be impersonated and hence there will be serious consequences [5]. On the other hand biometric features like fingerprint, iris, palm and face are not easily reproducible. Human are born with them and impossible to copy from others. Many features like face don't need physical contact with the examining device. With the growth of computing power and artificial intelligence the industry and research institutes are getting attracted more and more in this field of research. Web giants like Google, Apple, Facebook, and Amazon continued developing their own biological systems. In 2014, Gaussian Face algorithm developed by the researchers at The Chinese University of Hong Kong, achieved accuracy score of face recognition as 98.52% [6]. Deep Face by Facebook achieved accuracy of 97.25% in distinguishing similar face photographs [7]. "Face Net" by Google achieved accuracy of 99.63% on Labeled Faces in the Wild (LFW) dataset [8]. Any face recognition system primarily involves the following basic steps [9]. Step-1) Acquire Image/Video by high quality digital camera, surveillance cameras.Step-2)Face Detection with algorithms like Haar cascade classifiers to identify, localize and segment the faces in an image[10]. Step-3) Face normalization by preprocessing like scaling, rotation, de-noising etc [11]. Step-4) Feature extraction by one or more algorithms. This step uses feature engineering techniques like principal component analysis (PCA), linear discriminant analysis (LDA), independent component analysis (ICA) , Local binary pattern (LBP) , histogram oriented gradient (HOG) [12,13,14,15,16] etc. PCA is widely used in literature for face recognition with Eigen faces. Step-5) Feature matching with a labeled face database where each image involves a set of face features and the corresponding face label. Multiple instances of a face are stored with different facial expressions. Whenever a test image is given to the system features are computed and classical similarity measure like Euclidean, Manhattan, Mahalanabis distance can be used to find the closest match [17]. In addition machine learning (ML) and deep learning based models are also employed [18, 19]. This work is particularly involved in application of ML models in face recognition with two important feature engineering techniques. Rest of the work is distributed as follows. Section-II does the field study, Section-III describes the materials and methods needed, Section-IV is involved in the result and discussion of the experiment and Section-V concludes the study with future direction

II. RELATED WORK

This section studies the work that has been done in the area of face recognition.

R. Vinodini et al. used methods with PCA feature and recognition with neural network or support vector machine (SVM) [20]. Euclidean distance was used as similarity

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measure. K-nearest neighbor (kNN) classification was also used with PCA features. Ordinary PCA with Euclidean distance had given 30% accuracy, PCA combined with SVM had shown 70% accuracy and PCA with kNN performed with 92.5% accuracy using ORL dataset.

Narayan T Despande et al. method used Viola-Jones algorithm to detect human face [21]. After that PCA features are extracted which are used to train and test an artificial neural network (ANN). 94% accuracy was achieved with fusion of PCA and ANN using Bio-ID dataset.

Y. Shatnawi et al. method used PCA by taking first 50 Eigen-vectors as features and fed the vector to extension neural network(ENN) for training and testing[22].To calculate similarity the distance of one point was computed from a range of values called extension distance. The ENN is a fully connected neural network with m inputs and nc (no of classes) outputs. Two weights for upper and lower dimension were assigned for each connection. MLP of 50 inputs, a hidden layer of 100 neurons and output layers of 50 neurons were used. An accuracy of 75.04% was achieved for 10 different runs with Georgia Tech dataset. Optimum reported learning rate was 0.23 with accuracy 82% having 30 epochs.

L. Machidon et al. amalgamated the advantage of PCA in dimension reduction and tried reduced computation of PCA using geometrical approximated PCA (gaPCA) using three datasets [23]. Inverse Euclidean similarity score was used for first two datasets (Yale and Cambridge) while neural network was used for LFW. gaPCA first identifies two points {x11,x12} out of a set of points P1={p11,p12, ,…} with maximum Euclidean distance. A set of basis vector has to be calculated V={v1,v2,…, vn} where v1=(x11-x12). Compute midpoint m=(x11-x12)/2. v2 was computed by projecting all members of P1 onto hyperplane H1 with normal vector v1 that includes m. A set of projection was generated as P2={p21,p22, ….}. So every i-th basis vector was generated by projecting the points in P(j-1) onto hyperplane H(i-1), finding two elements with maximum distance and computing the difference. With Yale dataset gaPCA accuracy was 73.33% whereas PCA yielded 76.66% accuracy. With Cambridge dataset their gaPCA accuracy was 93.33% whereas PCA was 94.14% accurate. PCA and gaPCA achieved mean accuracy of 77% and 75% respectively for LFW dataset.

Zafaruddin et al. used PCA with neural network with ORL dataset [24]. A separate neural network was trained for every person. A test face was applied PCA and fed to all the neural networks. The network having maximum output greater than a threshold indicate a match. Histogram equalization was used in preprocessing phase. Maximum recognition rate reported was 93.3% with 70 Eigen vectors and 20 neurons in hidden layer. Hidden layer neurons and number of Eigen vectors were varied.

Anggo et al. used first PCA and then LDA (Linear Discriminate Analysis) to obtain face features [25]. PCA reduced dimension but it lost discriminant information needed for LDA. 50 students with 5 expressions were taken for the experiment with 93% accuracy.

I.U.W. Mulyono et al. compared Eigen face method on different benchmark dataset like Yale, JAFFE, ESSEX etc [26]. Reported accuracy varied from 67% to 100% with mean accuracy of 85%. PCA features were extracted from grayscale version of the input color images. Projection was used to reduce dimension. Euclidean score was used between projected test image and dataset images to find similarity. The method achieved 100%, 90% and 67% accuracies for ESSeX, JAFEE and Yale datasets respectively.

Battacharya et al. used Fishers LDA method [13]. Author argued that LDA has advantage over PCA as it maximizes the ratio of determinant of inter class and within class scatter matrices. Accuracy achieved was 92.5 % for ORL dataset.

III. MATERIAL AND METHODS

The proposed methodology starts with two important feature engineering techniques namely Principal Component Analysis (PCA) and Discrete Wavelet Transform (DWT). Afterwards the features are combined and fed into seven different Machine Learning models namely K-NN, Logistic Regression, Decision Tree, Random Forest, Support Vector machine, Naïve Bayes and Ridge Classifier. Finally the performances of the models are evaluated. The detailed outline is provided in Fig.1.

A. Extraction of PCA features

To recognize a face, the pixel values face images as treated as input features to the ML models. For a grayscale image of size 256X256 the numbers of features produced is 65536 which is huge. So PCA [13] is used here to reduce the dimension. It de-correlate the pixels of input image and compute only first few significant principal components. Singular Value Decomposition (SVD) [27] technique is used here to achieve PCA. Initially each face, as shown in Figure 2(a) is converted to one dimensional column vector. These vectors assembled into a two dimensional matrix F. Thus, if the face dataset contains 165 images each of size 256X256 then the matrix F will be of size 65536X165. Now mean face as shown in Fig 2(b) is calculated from matrix F which represents a face containing common features of all the faces. Then this mean face, represented as column vector is subtracted from all the columns of matrix F. After subtraction the new values in F represents the unique face features of each face.The matrix F is then applied singular value decomposition to get three matrices U, S and V^T.

$$F = U \sum V^T \tag{1}$$

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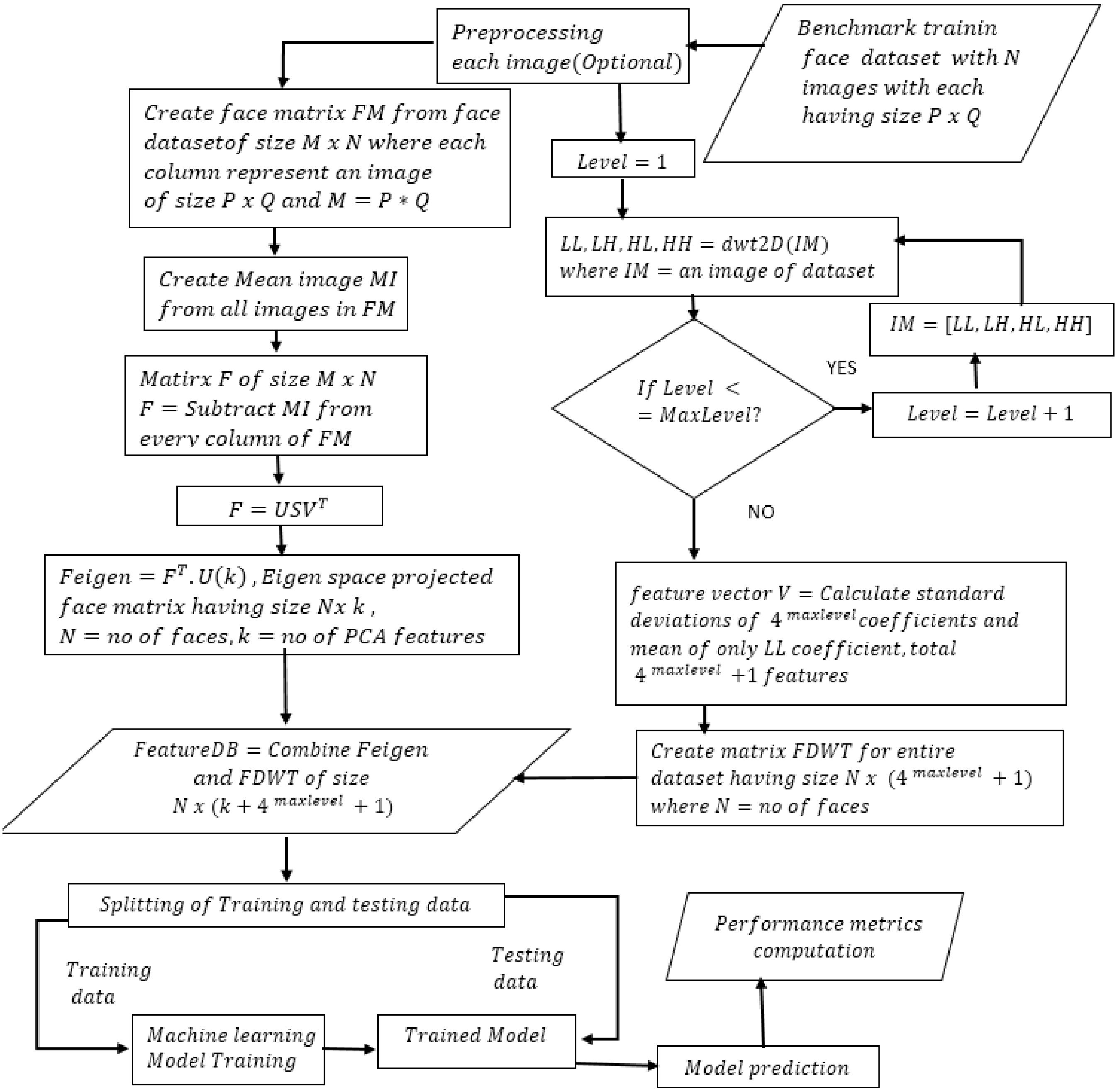
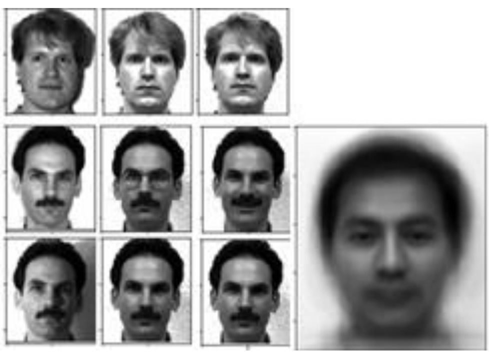


Figure 1. The workflow of the proposed method

If F is rectangular matrix of size mxn then U is an orthogonal matrix of size mxm such that $UU^T = I$, where I is identity matrix and the columns in U are orthonormal eigenvectors of FT. Similarly V is orthogonal nxn matrix with VVT=I and rows of VT are eigenvectors of FTF. The matrix $\sum$ is diagonal and it has size mxn. The diagonal values $\sigma 1, \sigma 2, ...\sigma p$ in $\sum$, called singular values, are the square roots of the non-zero eigenvalues $\lambda 1, \lambda 2, ...\lambda p$ of both FFT and FTF and are sorted in descending order i.e. $\sigma 1 > \sigma 2 > .... > \sigma p$ with p as rank of the matrix F. Variation of singular values and energy with respect to principal components are shown in Figure 3.



(a) (b)

Figure 2. (a) Some Representative faces in the Yale-dataset. (b) An example of mean face of Yale dataset.

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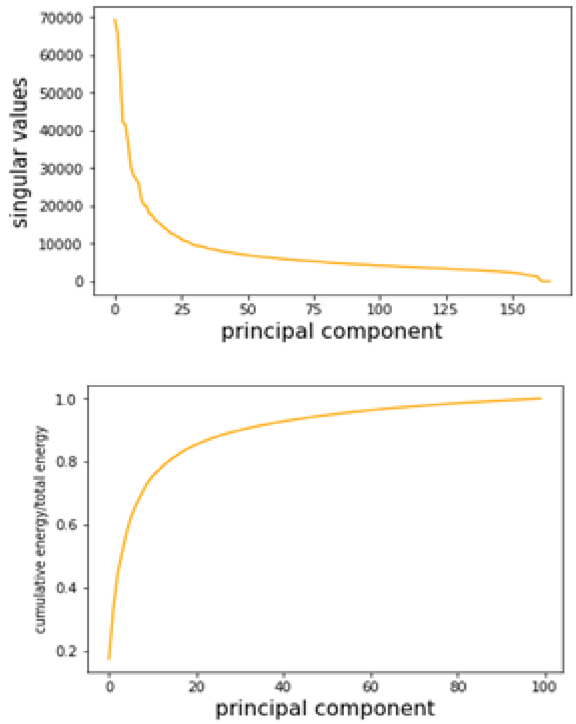

Figure . 3 (a) and (b)

Figure 3. (a) Singular curve (b) Cumulative energy curve with respect to principal components in Yale

The each column u1, u2,…, and um of U are the eigenvectors of FFT, will be seen as a ghost face called Eigen-face as in Fig.4. The u1 called first principal component corresponds to Eigen-value λ1, u2 called 2nd principal components corresponds to λ2 and so on. U as a whole represent Eigen-face space. The first k principal components U(k) are used to project all the images of F into low dimensional k-Eigen space. This is achieved by computing dot product of the FT and U(k).

$$Feigen = F^{T} \circ U(k) \tag{2}$$

Here the size FT is nxm size of U(k) is mxk ,so Feigen has size nxk. So n images in the dataset will be represented as k sized vector reducing dimension. The inverse transform from eigen-space to approximated original image space can be achieved by taking the dot product of U(k) and FeigenT followed by mean face addition.

$$F^{approx} = U(k)^{\circ} Feigen^{T} + Face^{mean} \tag{3}$$

Dimension of U(k) is mxk, FeigenT is kxn Hence dimension of Fapprox is mxn. This is an approximation of the original, as all the principal components is not taken into account.

B. Extraction of DWT Features

Discrete wavelet transform (DWT) is a signal processing technique used to analyze discrete signal by using scalingand wavelet functions [28]. Wavelet can dilate or compress and shift over time. The compressed wavelet can detect details and dilated form detects average components of a signal. There are many standard wavelets like Haar,

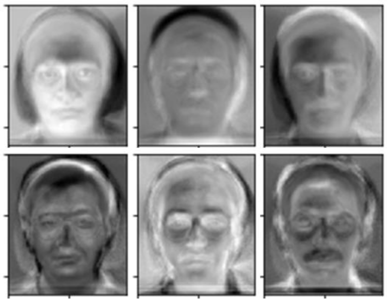

Figure 4. Some representative of Eigen faces of Yale dataset.

Daubechies, Morlet etc. DWT can be implemented using filter banks and can do multilevel decomposition of a signal. DWT for images can extract unique features. An image IM of size mxn is first decomposed into level-1 sub-bands LL, LH, HL and HH, each of size m/2 x n/2. LL represent average coefficients whereas LH, HL and HH components represent horizontal, vertical and diagonal detail coefficients respectively. The LL component can further be sub-divided into level-2 LL, LH, HL and HH sub-bands each of size m/4 x n/4. This process can be continued for any LL sub-band at level k to decompose into level k+1 sub-bands producing a hierarchical decomposition. Finally at the end of decomposition process one approximation component and many detailed components are generated. The statistical features like mean, standard deviation, skewness, kurtosis etc. for each sub-band can be used [29]. The histogram analysis reveals that the values of approximation coefficients are positive but detailed components have both positive and negatives coefficients which distributed symmetrically with zero center. So instead of taking mean standard deviation is more sensible choice. So mean value for LL and standard deviation for all the other coefficient are taken as features. Hence there will be 4^{lmax}+1 features will be generated for lmax level decomposition.

C. Combination and Normalization of features

For each image in the dataset the k PCA features and 4lmax+1 DWT features are combined together to form a feature vector of size (k+4lmax+1). So for n images in the dataset nx(k+4lmax+2) feature matrix will be generated having a label for each face For example if 100 PCA features and level 2 decomposition are taken then 117 features will be used for each face. The features are then normalized by taking z-score to minimize scale difference of features.

D. Training and Testing of different machine learning models

After normalization, the combined features of PCA and DWT are used to train and test seven predictive machine learning models namely k-NN, Logistic Regression, Decision Tree, Random Forest, Support Vector machine,

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Naïve Bayes and Ridge Classifier. Initially the standard train-test-split method e.g.70%-30% split were used to evaluate the accuracies of different models. But basic train-test-split methods show high variance in accuracy. This happens because each time random selection is made for 70% training and 30% testing data from the same dataset, the probability of selecting the identical training and testing dataset is nearly zero. To reduce this high variance in testing accuracy k-fold cross validation is recommended [30]. Accuracy of a machine learning model also depends on the hyper parameters of the model, so this experiment also tuned model hyper parameters for enhanced accuracy.

E. Training and Testing of different machine learning models

The classification metrics to gauge model performance as listed below.

a) Model accuracy is defined as the ratio of number of correct classification and total number of classification.

$$Accuracy = \frac{\#TP + \#TN}{\#TP + \#FP + \#TN + \#FN} \quad (4)$$

,where True Positive (TP) mean the predicted class is positive when the actual class is also positive, True Negative (TN) tells us that the predicted class is negative when it is actually negative, False Positive (FP) states that the model predicted positive when it is actually negative and False Negative (FN) express that the model predicted negative when it is actually positive. So sum of #FP and #FN gives us total number of misclassifications.

b) ROC (Receiver Operating Characteristics) curve

It helps in visualizing the performance of a classification model [31]. It shows model efficiency in detecting TP while avoiding FP.

$$True\_Positive\_Rate = TPR = \frac{TP}{TP + FN} \quad (5)$$

$$False\_Positive\_Rate = FPR = \frac{FP}{FP + TN} \quad (6)$$

In ROC curve,0<=FPR<=1 is plotted against 0<=TRP<=1 at different classification thresholds. This curve indicates predictive quality of the model. The Area Under Curve (AUC) is a 2D space under ROC curve which lies in between (0,0) and (1,1). AUC value ranges from 0 to 1. A value 1 indicates a perfect classifier and less than 0.5 indicates the model is useless.

Table 1. Performance of different ML models on four data sets.

Method	Data Sets	Accuracy (%)						
		k-NN	Logistic Regression	Decision Tree	Random Forest	Support Vector Machine	Naïve Bayes	Ridge Classifier
Train-Test Split (70%-30%)	YALE	80	86	80	86	88	64	98
	JAFEE	90.9	97.6	88.3	97.6	97.67	88.3	100
	GEORGIA TECH	56	75	36	68	74	64	76
	ORL	93.3	85.8	51.6	90	98.3	73.3	94
10 – Fold Cross Validation	YALE	60.9	83.7	58.13	87.8	81.2	69.7	90.72
	JAFEE	93.9	98.4	87.9	96.08	96.39	91.09	99.68
	GEORGIA TECH	61.7	83.4	43	76.9	83.7	72.8	83.9
	ORL	85.1	96.4	68.9	96.7	96.6	94.7	96.25
10—fold Cross Validation after Tuning Hyper-parameters	YALE	69.80 AUC=0.84	94.54 AUC=0.99	62.94 AUC=0.81	89.25 AUC=0.99	81.23 AUC=0.99	81.17 AUC=0.98	92.54 AUC=0.99
	JAFEE	95.18 AUC=0.94	99.5 AUC=0.99	89.3 AUC=0.94	97.6 AUC=0.99	97.67 AUC=1	100 AUC=0.99	99.84 AUC=0.99
	GEORGIA TECH	74.8 AUC=0.92	84.6 AUC=0.97	35.2 AUC=0.74	79.5 AUC=0.98	82.6 AUC=0.98	74 AUC=0.97	84 AUC=0.98
	ORL	96.3 AUC=0.97	96.7 AUC=0.99	56 AUC=0.88	98.5 AUC=0.99	96.6 AUC=0.99	97.2 AUC=1	96.3 AUC=.99

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IV. Results and Discussion

Performance of all ML models are evaluated using four standard face data sets, namely, Yale, JAFEE, Georgia Tech and ORL. The Yale dataset [32] contains 165 images of 15 different persons with each person having 11 different facial expressions, JAFFE (The Japanese Female Facial Expression) dataset [33] has facial images of 10 Japanese women, with 213 selfie images, Georgia Tech face database [34] has 750 images of 50 people and Cambridge ORL [35] (Olivetti Research Laboratory) face dataset contains a set 400 images of 40 people each with 10 different facial expressions.

A. Results

The results of basic train-test split, 10-fold cross validation and 10-fold cross validation with tuned hyper parameters are listed in Table 1. The tuned parameters used in Table-2 are utilized to get results in Table 1.

Table 2. Tuning of Hyper parameters.

Tuned Model	YALE	JAFEE	GEORGIA TECH	ORL
KNN Classifier	metric=Manhattan n_neighbors= 1 weights=uniform	metric=Manhattan n_neighbors=1 weights= uniform	metric= Euclidean n_neighbors= 3 weights=distance	metric=Manhattan n_neighbors= 1 weights= uniform
Logistic Regression	C=10 penalty=l2 solver= liblinear	C=100 penalty=l2 solver= liblinear	C= 0.1 penalty= l2 solver= liblinear	C= 0.1 penalty= l2 solver= newton-cg
Decision Tree	max_depth= 9	max_depth=9	max_depth= 9	max_depth= 9
Random Forest	max_features= sqrt n_estimators= 1000	max_features= sqrt, n_estimators= 1000	max_features= log2 n_estimators= 1000	max_features=sqrt n_estimators= 1000
Support Vector	C= 0.01 gamma= scale kernel= linear	C=50 gamma= scale kernel= linear	C= 50 gamma= scale kernel= linear	C= 50 gamma= scale kernel= linear
Naïve Bayes	var_smoothing=0.35	var_smoothing= 0.35	var_smoothing=0.12	var_smoothing= 0.19
Ridge Classifier	alpha= 0.8	alpha= 0.1	alpha= 0.9	alpha= 0.1

B. Analysis and Comparison of the result

Performance of the proposed method is compared with other existing state of the art face recognition methods and are listed in Table 3. It can be observed that, for YALE data set the proposed method achieve high accuracy of 94.54% which is better than [23][26]. The proposed method performs best on JAFEE data set and achieves 99.7% accuracy and is better than [26]. For other two datasets Georgia Tech and ORL proposed method outperformed the existing techniques. Thus it can be concluded that the combination of PCA and DWT features along with parameter tuning and cross validation become effective in face recognition

Table 3: Performance comparison

Data Set	Method	Technique Used	Accuracy
YALE	L. Machidon [23]	gaPCA combined with Neural network	73.33
	I. U. W. Mulyno [26]	Eigenface	67
	Proposed method	Fusion of PCA and DWT with Machine learning models	94.54 (Logistic regression)
JAFFEE	I. U. W. Mulyno [26]	Eigenface	90
	Proposed method	Fusion of PCA and DWT with Machine learning models	99.5 (Logistic regression)
GEORGIA TECH	Y. Shatnawi [22]	PCA combined with Extension neural network	82
	Proposed method	Fusion of PCA and DWT with Machine learning models	84.6 (Logistic regression)
ORL	R.Vinodini [20]	PCA	30
		PCA combined with SVM	70
		PCA combined with Neural network	92.5

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	Zafarrudin [24]	PCA combined with Neural network	93.3
	Bhattacharya [13]	LDA	92.5
	Proposed method	Fusion of PCA and DWT with Machine learning models	98.5 (Random forest)

V. Conclusion

In this work, machine learning models with combined features derived from PCA and DWT are used for human face recognition and are evaluated using four standard face data sets. From experimental observation it can be concluded that there is no universal model that gives best result across all the datasets and the accuracy of a model also depends on the dataset under consideration. But models like Logistic regression give consistently good results across all datasets. On the other hand decision tree model performs worst in all the dataset. Ensemble model like Random forest also shown a consistent performance. In most of the cases K-fold cross validation achieves better accuracy with respect to normal train test split method. This work can be extended further with the following direction in future a) Convolutional neural network or other modern deep neural networks can be used in place of ordinary neural network. b) Possibility of building a universal model that provides best result irrespective of datasets. c) Some additional preprocessing stuff like histogram equalization, face localization and orientation correction etc. may be incorporated to reduce initial errors. d) More feature engineering techniques can be exercised in future for better accuracy.

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