International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-7, Issue-6, March 2019

A vital SVKPCA Feature Set for Robust FRS with Ensemble Neural Network Classifier

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Abstract*: Face is the robust biometric in the field of access control and recognition. In this paper FFT Set, HARA Set, FHA Set, FHAKP Set and SVKPCA set are the five facial feature sets which was formed from spatial and frequency domain are analyzed using ensemble Neural Network to design a robust FRS. The ORL, NIR and Indian face databases are used to perform the experiments to prove that the proposed singleton SVKPCA set gives promising results irrespective of many challenges existing in the face databases. Following are the challenges faced by the feature set: gender, pose, expressions, scale and timing. The Neural classifier used in this proposed work incorporates the ensemble approaches of bagging and boosting to enhance the accuracy of the FRS from its regular standard model.

Index Terms*: Face Recognition System, Neural networks, Boosting, Bagging.

I. INTRODUCTION

Security and surveillance are the most important factors needed in every ones day-to-day life to survive peacefully in the world. As the security strategies increases, the threat towards it also increases, that urges the humankind in need of technically secured social life. This is possible with biometric verification and identification. Biometric works with the features that can be obtained from the physical and the behavioural characteristics of the human. Various physical biometric are in practice for recognizing human. Among all the existing biometrics, face is more advantageous than other biometrics [14][15] such as iris(eye), palm print, finger print, DNA etc., because of its reliability and availability. Face verification and identification are the major applications of FRS (Face Recognition System) and that is useful in the field of forensics and surveillance. Feature extraction and classification[11] are the two vital phases involved in the FRS. Researches are probably done on the extraction of the best features and effective classifiers to design a reliable FRS. The performance of FRS model is proved for its better accuracy with the diverse face databases that are globally available for research on free or under some terms and conditions. The face databases incorporate different challenges such as age[16]-[17], pose[20], blur[18], illumination[8],[10], occlusion [22], make up [23], facial surgery[19] etc. There are many feature extraction methods are available under spatial domain and frequency domain to overcome these challenges and to build an unblemished FRS. PCA (Principal Component Analysis)[5],[10],[21],[25], KPCA(Kernal PCA)[27],[28], Haralick features[13] and LBP (Linear Binary Pattern) [1] are some of the feature extracting methods under spatial domain. Under frequency domain, frequency vectors are acquired by FFT (Fast Fourier Transform) [4],[9], DWT(Discrete Wavelet Transform)[8] and DCT(Discrete Cosine Transform)[11] transformation methods from the face images. Among various features, robust features or feature sets are in demand for designing effective FRS. In this paper, the existing FRS related to the proposed feature sets are discussed in section 2. Formation and organization of facial data set are analyzed in the section 3 and the robust classifier Neural Network for enhancing the performance of FRS is discussed in the section 4. The experiments and results observed with diverse feature sets from diverse face data bases with the ensemble classifier Neural Network are recorded in section 5. The Section 6 includes the conclusion of the proposed work.

Revised Manuscript Received on 30 March 2019.
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II. RELATED WORKS

Research is going on various facial features and classifiers to build a robust FRS in order to overcome the challenges that diminish the performance of the FRS. Feature extraction and classification are the two vital phases of FRS, which is to be concentrated in order to enhance the performance of FRS. In this session, the recent FRS model related to the proposed analysis work and its performance are discussed in detail.

A. Local Binary Patterns Histogram (LBPH) with Back Propagation Neural Network (BPNN)

Usually, a digital image consists of huge volume of data that needs reduction technique to avoid complication in computations. LBPH is an efficient technique that reduces the image dimension and act as feature extractor in image analysis and diagnosis. Mohannad A. Abuzneid et al.[1] proposed a Modified LBP(MLBP) operator that gives better accuracy for face images in FRS than with the traditional LBP operator. In their work, initially histogram is used to store the local patterns, which are obtained by using traditional LBP and are stored in to bins equal to the number of uniform patterns acquired from the face image and one bin exclusively maintained to store all the other non-uniform patterns.

Each face is represented by a histogram where the bin sizes are high when patterns that are more similar are occurred. This process reduces 256-dimensional decimal to a 59-dimensional histogram, which again is refined as T-data set and that are fed in to BPNN classifier for classification process. The FRS that was designed by Mohannad A. Abuzneid et al. with LBPH and BPNN are analyzed on ORL dataset and 98% of the recognition rate was obtained.Baochang Zhang et al.[31] proposed a novel feature extracting technique DBC(Directional Binary Code) which uses slightly similar coding technique of LBP. It is specially designed for NIR face dataset, which incorporate real time FRS challenge, by Hong Kong Polytechnic University. Compare to LBP this new spatial based DBC produce information of the face edges more effectively by generating directional-based binary code for each region. This process is carried out by splitting the global face image in to regions with different circular shape and then the histogram of the image is classified by histogram intersection similarity measure (HISM). This approach of DBC based features with HISM classifier produced 94% accuracy, which can be further improved to 97.6% of accuracy by preprocessing the face images of NIR dataset with Gabor filter.

B. Bagging and boosting approaches on Neural Networks(NN)

The dataset organized for classification process using the Neural Networks classifier undergoes two consecutive steps of training and testing. The procedures of splitting the dataset into two partitions in classification can be of different sizes. Training data with less percentage of the dataset and producing high accuracy is more appreciable. Breiman proposed a bagging approach that inherits the concept of bootstrap sampling[3]. This approach forms several diverse training subsets from the original training dataset. These training subsets are then fed into diverse NN models and the performance is calculated by the majority of the total outcomes. Boosting is another approach which was formulated by Schapire. A best NN model can be designed for a dataset using this boosting approach by refining the training dataset based on the tuple that scores high during classification. In this boosting approach,[34] multiple classifiers are designed at multiple levels by concentrating on the weak tuple of the training dataset. Each level the performance of the classifier is improved so that the final level classifier scores high accuracy. Deepak Ghimire et al. [2] in their work extracted the facial features by HOG (Histogram of Orientation Gradient) technique from Japanese Female Facial Expression (JAFFE) dataset and the Extended Cohn-Kanade (CK+) facial expression dataset in order to identify the Facial expression with ELM (Extreme Learning Machine) that technique uses the bagging approach. Their experiments are carried out with seven classes of JAFFE and CK+ datasets and produced 94.37% and 97.3% respectively.

C. Eigen Facial Features with Neural classifier

Principal Component Analysis(PCA) is a traditional technique to extract feature vectors from spatial face data. Sutha et al.[5] in their proposed FRS used Hebbian learning in order to extract Eigen faces from the face database where these Eigen faces modified automatically when changes occurred in the face changes. The performance of their work reached 85% when their FRS model experimented with Yale database. Again Agarwal Mayank et al. [6] used a standard philosophy, where the number of Eigen faces are made equal to the number of face images in the training dataset with BPNN classifier, which produces 97.018% accuracy using the benchmark face dataset ORL. In their work for each person, a Neural Network (NN) model is created which gives positive output for the genuine person and negative output for fake persons. Also, Cheng-Yaw Low et al.[7] constructed an FRS model for real-time applications images like YouTube images with PCA and CNN (Convolutional Neural Network). Their FRS model is equipped with PCA Filter Ensemble Learning approach, which works with convolutional filter, and the accuracy is better because of using whitening PCA (WPCA) that compresses block wise histograms.

D. Frequency vectors for FRS

When Fourier transformation function applied to 2D images, the spatial data is converted into real and imaginary components[8]. The conversion of the face image in spatial domain f(x,y) of a 2D image into frequency domain F(u,v) which yields real R(u,v) and imaginary I(u,v) components which is given in (1). Here (x,y) is the spatial value and (u,v) states the frequency components of the face image.

$$\mathrm{F}(u,v) = R(u,v) + jI(u,v) \quad (1)$$

Wonjun Hwang et al.[8] worked with three types of Fourier domain namely real and imaginary component domain, Fourier spectrum domain and phase angle domain for their FRS model to overcome the illumination and expression variations more effectively. The Fourier spectrum domain(Γ) and phase angle domain (Φ) are expressed in (2) and (3).

$$\Gamma(u,v) = \sqrt{R^2(u,v) + jI^2(u,v)} \quad (2)$$

$$\Phi(u,v) = \cos\left(\tan^{-1}\frac{I(u,v)}{R(u,v)}\right) \quad (3)$$

Sujatha et al.[4] in their work formed a hybrid feature set by combining histogram features and Fourier magnitude features for their proposed FRS. They focused on three benchmark face datasets of JAFFEE, ORL and Indian datasets that produced better accuracy with their proposed FRS model with the Euclidian Distance classification metrics.

III. PROPOSED WORK

A. Formation of Feature Sets using Diverse Features

Feature extraction, feature selection, and classification are the important three phases in the face recognition process. Familiar features like FFT features[8], Haralick features[13], and PCA features[5] are extracted from the benchmark face databases such as ORL[29], NIR[32], and Indian[33].

In our proposed model, various feature sets are formed with the above said standard feature extraction techniques. Statistical measures such as energy, entropy and mean are applied on the frequency vectors[8] of FFT, thus the three features are formed on the basis of Fourier vectors in order to form the first feature set FFT Set. Angular second moment, contrast, correlation, sum of squares, different inverse moment, sum average, sum moment, sum entropy, entropy, difference variance, difference entropy and information measures of correlation are the thirteen texture features extracted from the face images in order to form the second feature set HARA Set which are named after Haralick[3]. Third feature set FHA is formed by concatenating the first two-feature sets i.e FFT set and HARA set.

PCA is a statistical approach that reduces the number of face spatial data into eigenvectors. The performance of the PCA is enhanced by using polynomial kernel. It converts the low dimensional data to high dimensional data that allows extracting best eigenvectors. These Eigen vectors are sorted and a Single Vital Principal Component (SVPC) is extracted as a robust feature that form a singleton feature set which is called as SVKPCA. The FHA data set with SVKPCA singleton feature set forms the fourth data set FHAKP. Also the single feature vector SVKPCA act as the fifth feature set which works well with ensemble neural classifier and produces the best accuracy with less space complexity.

B. Frequency domain features

Generally, FRS suffers from various challenges like occlusion, translation, pose variation, illumination, scaling, and illuminations, which allows degrading its performance and restricting its utility in various applications. The usage of frequency vectors as the feature in FRS which can able to overcome the above-said challenges[9] and produces better accuracy. Real and imaginary components[8] of Fourier F(u,v) features are extracted from spatial image f(x,y) which is shown in (4) where u and v are the frequency variables. In the below equation X and Y are number of rows and columns of the face image respectively.

$$F(u,v) = \frac{1}{XY}\sum_{x=0}^{X-1}\sum_{y=0}^{Y-1} f(x,y)e^{-j2\pi\left(\frac{ux}{X}+\frac{vy}{Y}\right)} \tag{4}$$

In the proposed work, statistical metrics are applied on the frequency feature vectors similar to Randa Atta et al. [11] and Gracia et al.[12] FRS models. In their proposed work statistical calculations are done on frequency vectors which are obtained from DCT(Discrete Cosine Transform) and DWT(Discrete Wavelet Transform) respectively. Gracia et al.[12] extracted the feature vectors by calculating the mean and variance from the approximation bands and variance alone from the detail bands of DWT applied face images. When worked with ORL dataset this methodology of applying statistical metrics on DWT produced 93.5% with Nearest Neighbour classifier. In order to avoid working with more feature vectors Randa Atta et al.[11] proposed an FRS model in which DCT decomposition methodology is used to generate approximation and detail bands from face images. In each level of decomposition, an approximation is concentrated and set of non-overlapping partitions are made from which the mean, variance and entropy are calculated as feature vectors. This model with the ORL face database produced 97.5% of accuracy.

In the proposed work, the first feature set FFT set is formed by calculating statistical features mean, variance and entropy[11] on the Fourier transformed face images of the benchmark databases ORL, NIR, and Indian. The equations from (5) to (7) are used to find mean(μ), variance(σ) and entropy(H)[11] from the face images where M1 and N1 are size of the chosen face image f(x,y), where and number the histogram counts are denoted by ρ.

$$\mu = \frac{1}{M1N1}\sum_{y=1}^{M1}\sum_{x=1}^{N1}(f(x,y)) \tag{5}$$

$$\sigma^2 = \frac{1}{M1N1}\sum_{y=1}^{M1}\sum_{x=1}^{N1}(f(x,y)-\mu)^2 \tag{6}$$

$$H_{ij} = -\Sigma\big(\rho * \log_2(\rho)\big) \tag{7}$$

C. Texture domain features

In 1973, Haralick et al.[13] extracted fourteen texture features from the different type of images like photomicrographs, aerial photographs and satellite images for the purpose of identifying objects or interested region using a piecewise linear decision rule and min-max decision rule. The features extracted for their work are based on homogeneity, gray-tone linear dependencies complexity, contrast, number and nature of the boundaries of the image. The performance varies from 80% to 90% for the above said photographs. In the proposed work, the thirteen features that is suggested in the Haralick et al. work such as angular second moment, contrast, correlation, the sum of squares, different inverse moment, sum average, sum moment, sum entropy, entropy, difference variance, difference entropy and information measures of correlation are clustered as a HARA set. The third feature set FHA is formed by merging FFT set and HARA set to observe the performance of hybrid features from a diverse domain that is frequency domain and texture domain.

D. Extraction of Eigen values

PCA plays a vital role in forming the fourth and fifth feature sets of this proposed work. Extracting the eigenvalues and assigning the prime eigenvalue to each image is the main task of using PCA[7] in this analysis process. Initially, the collected M number of grayscale face images (I_i) where i ranges from 1 to M with NxN dimensions are converted into single column vectors (Γ_i). Then the face vectors are normalized(φ_i) by averaging the face vectors to find the mean of the face images(Ψ) and subtracting it with individual face vectors (Γ_i) which are shown in (8).

$$\varphi_i = \Gamma_i - \Psi \tag{8}$$

To obtain the eigenvectors a statistical measure covariance is utilized as shown in (9) where $A = \{\varphi_1, \varphi_2, \varphi_3, \ldots, \varphi_M\}$ and C is the Covariance.

The above covariance calculation is done in the low dimension space that produces very less number of eigenvectors where AA^T generates high dimension space eigenvectors. The low dimension space eigenvectors u_i are mapped into high dimension space eigenvectors v_i which is given in (10) where i =1,2,…r and r is the number of unique non-zero chosen eigenvectors.

$$C = A^T A \tag{9}$$

$$u_i = Av_i \tag{10}$$

The Eigen values(λ^i), which are the chief features of face recognition or any other image processing applications, are generated with respect to the eigenvectors u_i as shown in (11).

$$u_i = \frac{1}{\lambda^i} Av_i \tag{11}$$

The polynomial kernel $k(x_i, x_j)$ [27] is applied on the normalized face vectors to project low dimensional vectors into high dimensional vectors shown in (12). Here $(x_i x_j)$ is the ijth vector, which is transformed with d degree of polynomial. The non-linear vectors are separated much more effectively by this transformation and a single prime Eigen value is extracted for each face image by sorting and tracking the best Eigen values.

$$k(x_i, x_j) = (x_i^T x_j)^d \tag{12}$$

Thus, the traditional approach is applied to the images of the face database to collect the eigenvectors and it was sorted in descending order, then the single prime eigenvalue is collected to form the fourth and fifth feature sets of the proposed work.

E. Effective Ensemble Neural Network Classifier

Back Propagation Neural Network (BPNN)[26] is used for effective classification in FRS which undergoes supervised learning function with training and testing phases that are depicted in Fig.1 and Fig.2[7].

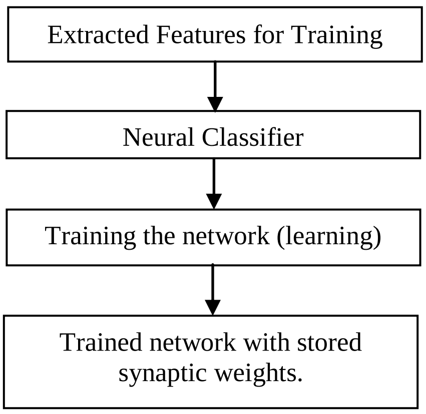

Fig. 1. Architecture of the NN training phase

During the training phase, the input face feature vectors are assigned to the target vector and the learning is performed by updating the weights until no more convergence in the error. This error is measured by finding the difference between expected and actual output vectors. In the testing phase, the untrained face feature vectors are tested with the trained network and the output accuracy is recorded.

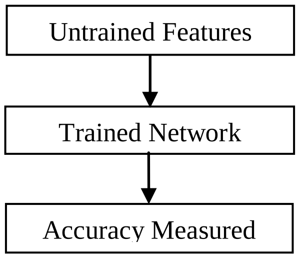

Fig. 2. Architecture of the testing phase

BPNN has different layers namely input layer, hidden layers, and an output layer with the diverse number of neurons in each layer that is shown in the Fig.3[34]. The number of input feature vectors used for a particular FRS, decides the number of neurons in the input layer. The neurons in the hidden layer are updated and its count is determined by the performance of the network. According to the number of output results, the neurons are fixed in the output layer.

BPNN[5][7] is a Multilayer perception in which the initial weights are randomly assigned between all the layers and uses a gradient descent algorithm for error convergence. If more than one hidden layer exists, then weights are also assigned between two hidden layers. In NN the weights are used to connect the neurons and that are updated using learning rules. Each iteration of the network can be labeled as epochs and BPNN uses gradient-based delta-learning rule for updating the weights that exist between the layers. The weights that are available in the links between the hidden layer and the output layer of BPNN are updated with respect to the error obtained in the output layer which is given in (13)[5][34]. Always the weight values range between zero to one and it excludes zero and one. The weights are adjusted with respect to the error rate thus the new weight is obtained by adding the old weight with the change of weight.

$$\Delta v_{jk} = \frac{\alpha\, \partial E}{\partial\, v_{jk}} \tag{13}$$

Here Δv_{jk} denote the change of weight between the hidden layer and output layer where k is the number of neurons in the hidden layer, j is the number of neurons in output layer and α is the learning rate. The change of weight depends on the net value of hidden units and output values. In the following equation(14) y_j is the obtained output and δ_j denote error rate that depends on the output layer.

$$\frac{\partial E}{\partial v_{jk}} = -y_j \delta_j \tag{14}$$

The error rate δ_j can be obtained from the expected output(ey) and obtained output(y), which is depicted in (15).

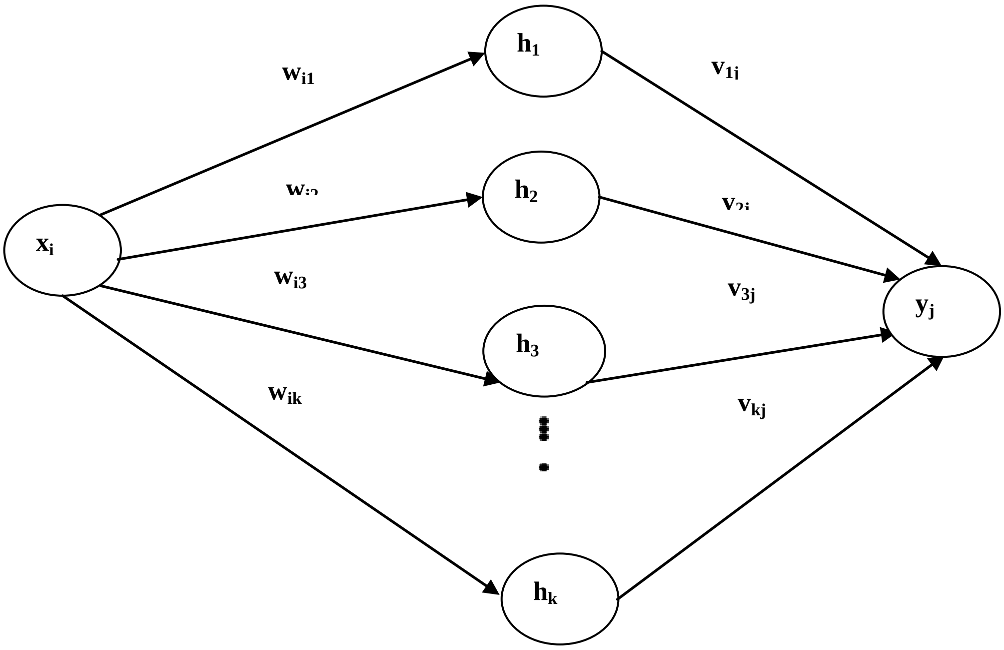

Fig. 3. Multilayer Feed Forward Neural network

$$\delta_j = (ey_j - y_j)\, y_j(1 - y_j) \qquad (15)$$

The weight between the input layer and the hidden layer can be updated with the following formula.

$$\Delta w_{kj} = \frac{\alpha\, \partial E}{\partial w_{ki}} \qquad (16)$$

The change of weight depends on input x_i and delta error rate δ_k.

$$\frac{\partial E}{\partial w_{ki}} = -x_i \delta_k \qquad (17)$$

The new weight(w_{new}) obtained is based on the old weight(w_{old}) and the change of weight as given in(18).

$$w_{new} = \mathrm{w}_{old} + \Delta w_{kj} \qquad (18)$$

Thus the neural network gets trained with the given inputs and expected outputs by means of sustaining weights lies between the layers. This trained network is then tested with the untrained samples and the accuracy is calculated using (19)[1].

$$Accuracy = \frac{Total\ number\ of\ correct\ match}{Total\ number\ of\ samples}\ X\ 100 \qquad (19)$$

F. Global face databases

Three globally accepted ORL, NIR and Indian face databases are used to evaluate the proposed FRS models. Olivetti Research Laboratory Dataset (ORL) [29] has the grayscale face images of size 92 X 112 pixels for forty different subjects (personalities) with ten samples for each subject which are varies in gender, pose, expressions and timing that is shown in the Fig. 4. The sums of four hundred face images are available in the ORL dataset, can be split into two sub-datasets for training and for testing.

Near InfraRed (NIR) face dataset[24][30][31][32] is a another open dataset in which the NIR light-emitting diodes (LEDs) are used as active radiation sources which are strong enough for indoor use and are power-effective. Nearly 100 samples are collected for every fifteen subjects which are collected within two months gap with different pose, time, scale and expressions. In the proposed work, twenty samples for each subject are considered for the experiments and the sample faces of NIR are shown in the Fig.5.

Fig. 4. A Sample ORL face dataset

Fig. 5. A Sample NIR face database

An Indian database[33] was created in the year 2002 by IIT Kanpur campus to support researchers with forty subjects. Gradually they come out with more subjects including challenges like pose and expressions in the homogeneous background and sample face images of Indian face database shown in Fig.6.

In the proposed work, twenty-one subjects from both male and female directories are collected and put together as forty-two subjects for the experiments.

Fig. 6. A Sample Indian face database

IV. EXPERIMENTS AND RESULTS

In the proposed research work, all the five feature sets FFT Set, HARA Set, FHA Set, FHAKP Set and SVKPCA set are extracted with MATLAB2017 from the face databases of ORL database, NIR database, and Indian Female database. These feature sets are analyzed with BPNN classifier using IBM SPSS Predictive Modeler. Training and Testing are the two processes done on the dataset where the data set is partitioned as 50% for training and 50% for testing. Different Neural models for FRS are constructed using three approaches like Standard Model(SM), BAGging model(BAG) and BOOSTing model(BOOST).

A. Experiment 1: ORL face database with BPNN

The feature sets are formed with the features extracted from ORL face dataset by Frequency transformation, PCA, textures and KPCA methods that are classified with ensemble BPNN. The accuracy of these feature sets are analyzed with different FRS models and depicted in the table I.

Table I: BPNN on ORL database Features

ORL database Features	Accuracy in %		
	SM	**BAG**	**BOOST**
FFT SET	14.1%	38.8%	39.1%
HARA SET	48.7%	84.6%	92.3%
FHA SET	64.9%	89.4%	95.5%
FHAKP SET	65.0%	93.3%	99.4%
SVKPCA SET	96.4%	99.2%	99.2%

The accuracy of FRS is too good when boosting approach is used with the NN classifier and observed that, BAG or BOOST approach are having high performance in the SVKPCA set comparatively with SM which is shown in Fig. 7.

B. Experiment2: NIR face database with BPNN

The experiment is also conducted with the feature sets obtained from the NIR face database with the diverse NN classifier model and the performance evaluation is shown in Fig.8. The experiments on NIR datasets are usually done to prove the efficiency of FRS model for real-time applications as the dataset is collected during two months. Again when analyzing the accuracy of the FRS models with NIR Face database features, the SVKPCA feature set is found to be the best feature set among all the other feature sets with all the three approaches of SM, BAG, and BOOST in Neural classifier which is shown in table II.

Table II: BPNN on NIR Face database Features

NIR Face database Features	Accuracy in %		
	SM	**BAG**	**BOOST**
FFT SET	41.7%	69.2%	73.9%
HARA SET	61.1%	90.8%	93.6%
FHA SET	73.2%	93.3%	98.5%
FHAKP SET	84.8%	96.6%	99.4%
SVKPCA SET	85.8%	97.9%	98.1%

The Fig. 8 shows obviously that the single feature vector SVKPCA set gives high accuracy when tested with the suggested three Neural approaches.

C. Experiment3: Indian face database with BPNN

The outcome of the experiment1 and experient2 proves that the KPCA set with diverse classifier approaches such as SM, BAG and BOOST models gives better results than with the feature sets created from frequency, texture and traditional PCA vectors. Taking to the next level of the experiment the feature set is formed from the Indian Face database and are classified with BPNN classifier and the accuracy is recorded which is shown in the table III and performance is depicted in Fig. 9.

Table III: BPNN on Indian Face database Features

Indian Face database Features Set	Accuracy in %		
	SM	**BAG**	**BOOST**
FFT SET	62.5%	75.6%	72.8%
HARA SET	47.7%	83.4%	88.2%
FHA SET	82.1%	95.0%	97.6%
FHAKP SET	88.4%	97.2%	99.3%
SVKPCA SET	98.4%	99.1%	99.3%

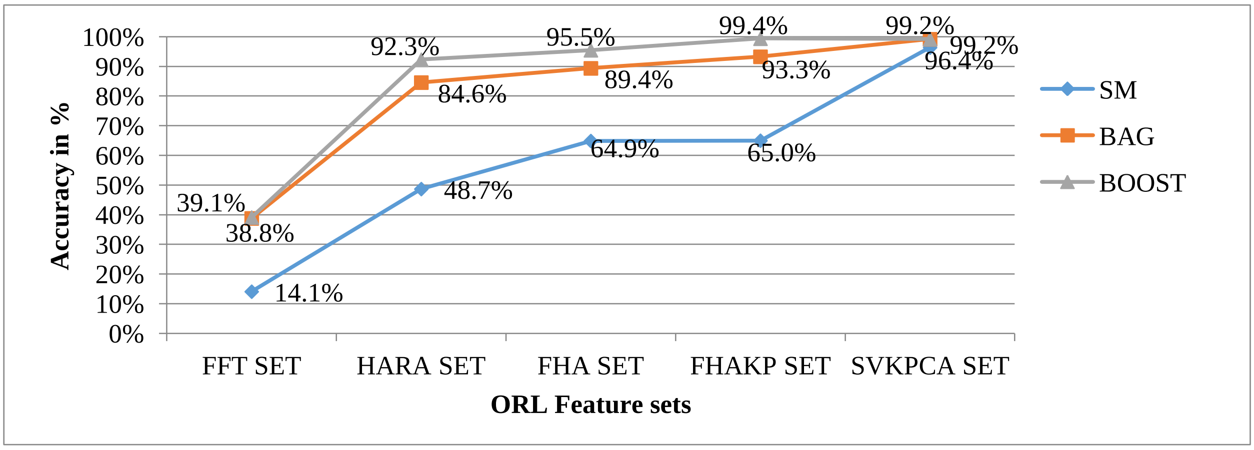

Fig. 7. Performance of BPNN on ORL database Features with diverse approaches

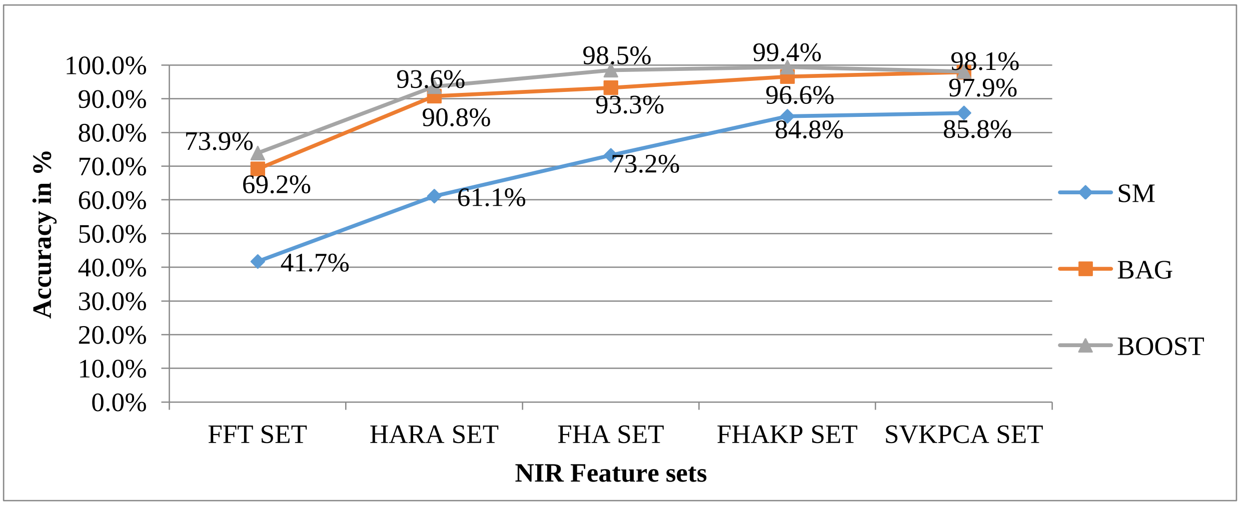

Fig. 8. Performance of BPNN on NIR database Features with diverse approaches

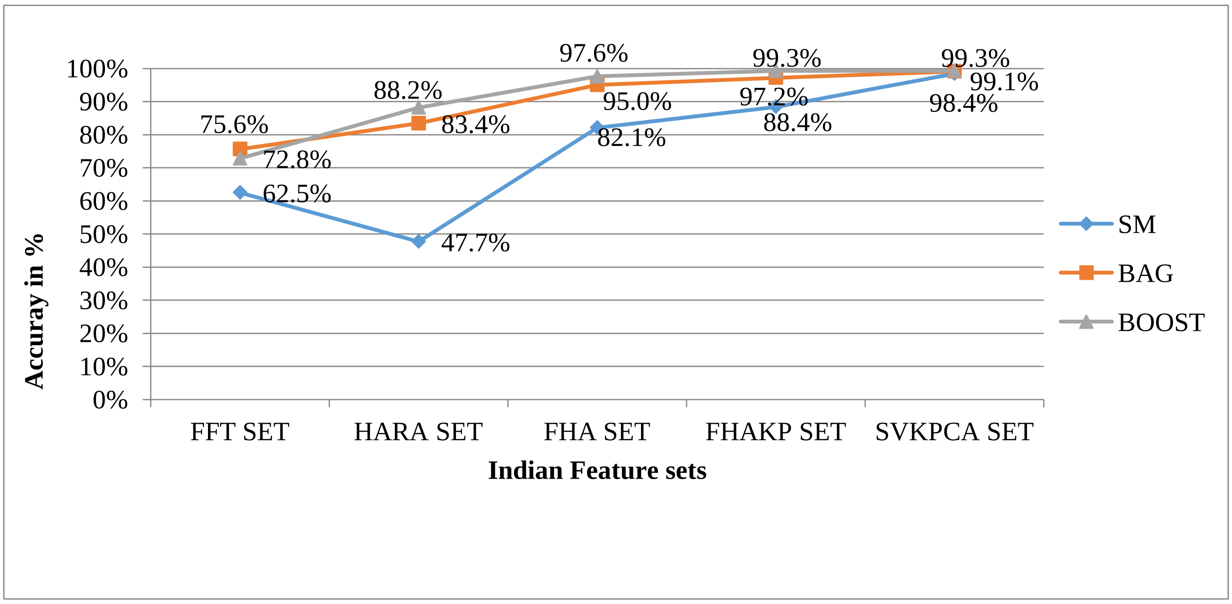

Fig. 9. Performance of BPNN on Indian database Features with diverse approaches

D. SVKPCA set vs. Existing features on ORL face dataset:

Facial feature analysis for constructing efficient FRS model is a long journey of investigation for verification and identification process. The singleton feature set SVKPCA scores high accuracy than the existing features extracted with traditional subspace methods like PCA, LBP and DBC. The performance of traditional feature extracting methods with Neural classifier on the ORL face database is high compared with SVKPCA feature set and the accuracy is observed which is shown in the table IV and Fig. 10.

Table IV: SVKPCA set vs. Existing features on ORL face database

S.No	Author	Technique and Face dataset	Accuracy
1	C. Garcia et al., [12]	DCT and DWT + KNN + ORL	93.5%
2	Cheng-Yaw Low et al.[7]	PCA + Hebbian Learing +ORL	97.0%
3	Mohannad A. Abuzneid et al.[1]	MLBP + NN +ORL	98.0%
4	Proposed Method	SVKPCA Set + NN + ORL	99.2%

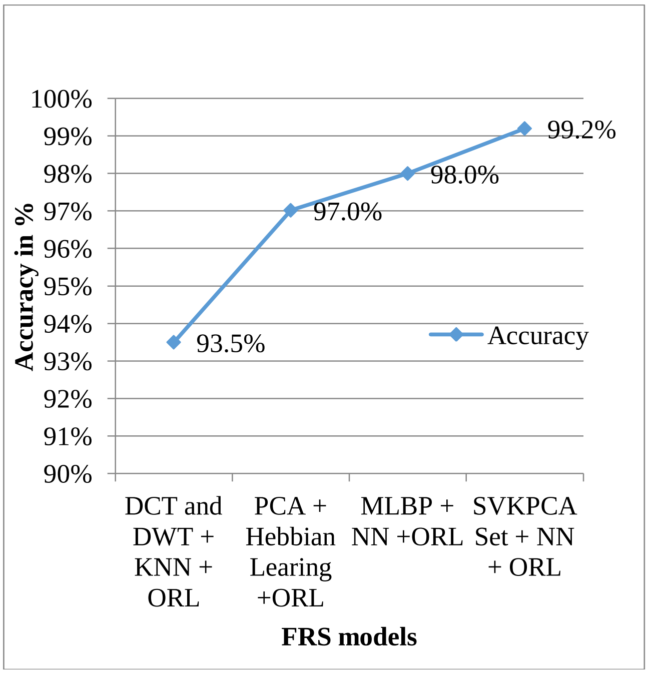

Fig. 10. SVKPCA set vs. Existing features on ORL face dataset

E. SVKPCA set vs. Existing features on NIR face dataset:

Facial feature analysis on NIR face database is inevitable since the motto of designing efficient FRS models is to apply the models for real-time applications. Baochang Zhang et al.[31] experimented NIR face database with different feature extraction methods such as PCA and DBC. The performance of this method is recorded as 97.6% of accuracy. The results produced by the proposed SVKPCA set model on NIR face database is 98.1% which scores better than Baochang Zhang et al. FRS model that is shown in the below table V and Fig. 11.

Table V: SVKPCA set vs. Existing features on NIR

S. No	Author	Technique and Face dataset	Accuracy
1	Baochang Zhang et al.[31]	Gabor + PCA + NIR	82.2%
2	Baochang Zhang et al.[31]	DBC + HISM +NIR	94.0%
3	Baochang Zhang et al.[31]	Gabor + DBC + HISM + NIR	97.6%
4	Proposed Method	SVKPCA Set + NN + NIR	98.1%

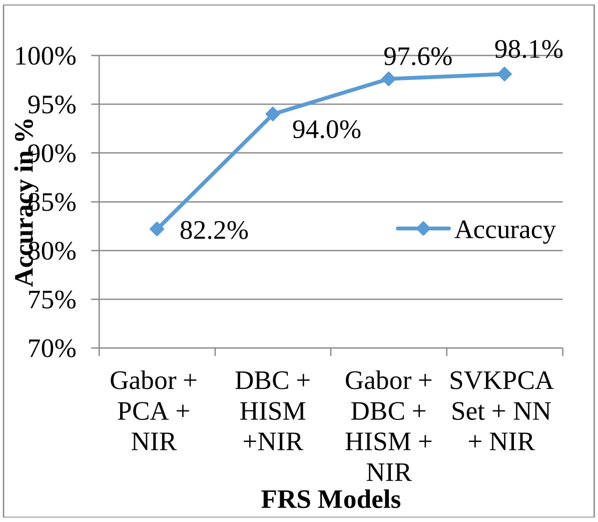

Fig. 11. SVKPCA set vs. Existing features on NIR face database

V. CONCLUSION

Feature extraction and classification are the core factors in FRS to build a better FRS for security and surveillance. In this paper, five features sets are obtained from three different face databases and classified with the ensemble Neural classifier. The FRS model designed with proposed SVKPCA feature set produced good results on all the three databases, even though the datasets includes wide range of challenges like pose, scale, time, expressions etc. The experiments concludes that among all the five feature sets, the proposed SVKPCA set scores high for all the three diverse face datasets. In addition, this feature set requires less space and time complexity.

ACKNOWLEDGMENT

We sincerely thank IBM for providing us with IBM SPSS Predictive Modeler as a free trial version, which helped us to analyze the face datasets more accurately.

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