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***Research paper***

# Improved facial feature sets for enhancing face recognition system

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**Abstract**

Face recognition is the vogue technology in the field of biometrics for providing surveillance facility, which is most needed in public and domestic places. With the upcoming robust algorithms for face recognition, following are the challenges noted and that have a major impact in facial recognition system such as illumination variation, pose, expression, weight variation, plastic surgery etc… that must be redefined by using long-lasting feature set and efficient classifier that suits well for the feature set.

In this paper, four efficient feature sets are formed by incorporating novel ideas on the fundamental traditional feature extracting methodologies such as KPCA (Kernel Principal Components), FFT (Fast Fourier Transform) and texture features which are collected from ORL (Olivetti Research Laboratory-AT&T) data base using MATLAB2015. The feature sets are analyzed with the classifiers like SVM (Support Vector Machine) and KNN (K-Nearest Neighbour) using IBM SPSS Predictive Modeler.

The feature sets are fine tuned for its accuracy with three different kernels of diverse gamma values during SVM classification process. In order to fix the best K neighbours during KNN classification on the four feature sets and SVPC feature, cross validation techniques with five and ten folds are done in order to attain the best k value, which produces better accuracy.

***Keywords***: *Classifier; Face Recognition System; Feature Sets; KPCA(Kernel Principal Components); ORL (Olivetti Research Laboratory) Data Base.*

## 1. Introduction

Biometric is the recent field technique which is needed in information technology for the purpose of security and surveillance. The biometric characteristic are based on physical and behaviour nature of the human which are used in identification and verification process in various applications like law enforcement, HCI(Human-Computer Interaction), surveillance, authentication[13] etc. Face, DNA, iris, fingerprint and palm print are the physical characteristics which are frequently used for verification and identification of human in the real time applications [7]. Gesture and keystroke are the well-known behaviour characteristics which are in practice among all the behaviour characteristics. In the biometric field, face attracts all kinds of users because of its reliability and availability. The important benefit in security issue of face biometric is, it can be captured without the user knowledge and co-operation. Plastic surgery[21], makeup, age[2][5], blur[4], illumination variation[12], poses[8], expressions[15], occlusions[14] and disguise are the existing challenges, that reduce the accuracy of recognizing face biometric [8][10][11][21]. PCA(Principal Component Analysis),LDA(Linear Discriminant Analysis), LBP(Local Binary Pattern), Histograms of Oriented Gradients(HOG), Haar-like rectangular features HOGOMs(Histograms of Gabor ordinal measures) [10] are the traditional and popular feature extracting algorithms. Emerging deep learning based features and multimodal features are strengthening the FRS (Face Recognition System) by means of combining the traditional features [10][11] with other techniques.

Classification is the final phase of the recognition process.The areas like pattern recognition, machine learning and forensics includes classifiers for creating a model for face recognition by training the tuples with class labels.The trained model is used for testing the new tuples.Accuracy will be high, if the testing samples are classified correctly under the respective classes.

The popular classifiers, that are used in the recognition process are KNN (K-Nearest Neighbour) classifier [12], Neural Networks [10], SVM [1] [18], random decision forest [9] [25], sparse representation [3] [8], linear regression classification (LRC) [16] etc. In the section two, the existing systems and its performance are explored. The proposed techniques that support the improved facial feature set and classifiers are discussed in section three. The proposed dataset and traditional extractors with different classifiers are examined in section four. Section five has the conclusion of the quality of the proposed features sets and classifiers.

## 2. Related works

In this section, the related works of proposed system are discussed.

### 2.1. Principal Component Analysis (PCA)

It is an unsupervised method in which statistical methods such as mean, standard deviation and covariance are involved to reduce the high dimensional data to low dimensional data. Shih-Ming Huang et al. has constructed a model with PCA in their work using the traditional PCA and improved PCA (iPCA) model by leaving first n number of principal components are obtained from the illumination variant images. The low frequencies facial data, which are affected with illumination issue, are dropped from the feature set, thus the result of their proposed work are improved. Linear regression model was constructed with robust coefficients for classification which has the accuracy of 82.8% on FERET face database. In Gopinath Mahale et al. work[13], the real-time Face Recognition (FR) module are carried out by applying Weighted Modular Principle Component(WPCA) for having discriminating features by modifying traditional PCA and classified with Radial Basis Function Neural Networks (RBFNN) and that contribute 450 face recognitions per second which gives better result than other real time applications. The researchers are worked on diverse face databases (AT&T Lab (ORL), Sheffield database and Yale data base) and produce high accuracy in classification with the percentage of 94.19% on Extended Yale database B database. N.Sudha et al. [29] proposed a method with the recognition rate of 85% which combine the principal components and hebbian learning model of Neural Network which was appropriate for any dynamic data bases that subject to change due to environmental changes while capturing the face images.

### 2.2. Kernel Principal Component Analysis (KPCA)

An eigenvector can be manipulated as a linear combination of training nodes, which can be collected as a subset. Xu Yong et al. proposed [17] a KPCA-based feature extraction method that generates discriminate nodes for the construction of the eigenvector subset with more information and that produce good accuracy in the recognition process. Firas AL-Mukhtar et al. in their research work [18], incorporated KPCA with polynomial kernel as feature extractor and used the classification technique as SVM. The fundamental idea behind their research work is to place the data collected from the facial images as PCA vectors in the high dimensional space and to enhance the accuracy up to 97.5% when classified with SVM (Polynomial) on ORL dataset.

### 2.3. Fast Fourier Transform (FFT)

The complex Fourier frequency components are extracted as real and imaginary components from 2D face images by applying fourier transformations [19]. In Wonjun Hwang et al. research work, hybrid Fourier features are extracted and classified with LDA (Linear Discriminate analysis) method and it has produced 81.49% accuracy with different illumination conditions and expressions of 2-D face images on FRGC version2.0 data sets. In Sujatha et al. research work the feature extractors DWT (Discrete Wavelet Transform), FFT and Compressed LBP(Local Binary Pattern)[30] are applied on ORL, Jaffee and Indian male or female face dataset are used in order to acquire facial features. These features are classified with Euclidean distance metric and the performance are analyzed with FAR (Falsely Accept Rate), FRR (Falsely Reject Rate), TSR (Total Success Rate) and EER (Equal Error Rate). TSR values on ORL data set are 83.33% and 90% with compressed LBP and FFT respectively.

### 2.4.Haralick features

Texture features gives the information about the surface with respect to the surrounding which are useful in discriminating one image from the other image. Homogeneity, gray-tone linear dependencies complexity, contrast, number and nature of the boundaries of the image are the areas where statistical features are extracted in the Haralick et al. research work [20] in order to classify the satellite image. In the above research work, thirteen textural features from different satellite images, which cause the variation in resolution, are acquired and the performance has been raised above 80% with less computational computations.

### 2.5. Support Vector Machine (SVM)

The support vector machine can be effectively applied for any type of problems with the suitable kernel functions that includes perfect gamma value to achieve the maximum accuracy. Marie Tahon et al. has used LibSVM tool in their research work in order to analyze the minimal feature set which handles the emotion recognition in the face datasets Li-174 and Os-384[15]. Selective acoustic feature set is validated with Cross-corpus optimization method, which produces promising results with optimized gamma value. Information gain and Gaussian mixture models with Bhattacharyya distance are two non-classification techniques that are applied on the feature set in order to evaluate the efficiency of the single feature or family feature set.

Face identification performance is improved because of the plastic surgery challenges emerging more vigorously in the field of machine learning.Multiple projective dictionary learning (MPDL) frameworks has been developed in the Naman Kohli et al. research work [21] and it excludes $l_0$ and $l_1$ norms and that reduce computational complexity.The cosine distance scores are measured in the plastic surgery area of the face by using of binary face descriptors of each identified areas are learned with SVM model and produced high accuracy of 97.96 percentage of on plastic surgery face dataset. Further the feature set is reduced with optimized SVM parameters.

### 2.6. K- Nearest Neighbour (KNN)

In KNN, prediction is done by comparing of testing tuple with the training tuple without generating a training model. The distance measured between the attributes of training and testing tuples are based on different distance metrics such as Euclidean distance, Mahalanobis distance [24], Chi-square ($\chi^2$) distance [6] etc., and K values [23]. Ezoji et al. worked on the challenges of illumination occurs in the facial images, which are collected from different environments. In their research work, features are extracted using quantized table model on DCT (Discrete Cosine Transform) which under goes polar decomposition in order to form a better feature space. Classification is done with Nearest Neighbour Rule by means of achieving the first best (K=1) match of testing record with training record when it considered as rank the first recognition rate. They have also concluded experimentally that, if K increases, recognition rate also increases. AR and Yale data bases were utilized for performance analysis and have scored hundred percentage accuracy.

## 3. Proposed work

In the proposed work, KPCA, FFT and Haralick features are added in the feature space for having hybrid feature set in order to improve recognition process.The dynamic classifiers SVM and KNN are more applicable for both linear and non-linear problems, and those techniques are chosen for improving the accuracy for the FRS.

### 3.1. PCA and KPCA

Standard deviation, covariance, eigenvectors and eigenvalues are the statistical metrics which are associated with the PCA for facial feature generation. The average value of the dataset is known as the statistical mean metric of the dataset which is expressed in the following equation (1).

$$\bar{A} = \frac{\sum_{i=1}^{n} A_i}{n} \quad (1)$$

Where $A_i$ are the attributes, whose values ranges from 1 to n and n is denoted as the number of elements of the attribute A.

In some occasion, the statistical metric mean is same for the different sets of data, hence the data distribution with respect to mean is considered for generating principal components because of its discrepancy in diverse datasets which is expressed in equation(2).

$$s = \sqrt{\frac{\sum_{i=1}^{n}(A_i - \bar{A})^2}{n}} \quad (2)$$

In the above equation, $\bar{A}$ is the mean and s is the standard deviation of $A_i$.

The spreading of data can also be measured with variance metric which works well on one dimensional (1-D) data set. The dimensionality issue of working with 1-D dataset can be improved with covariance metric and that can able to prune the unnecessary vectors. It is considered that, the spread of data with two or more attributes can be expressed in the following equation (3).

$$\mathrm{cov}(A, B) = \frac{\sum_{i=1}^{n}(A_i - \bar{A})(B_i - \bar{B})\ldots(N_i - \bar{N})}{n-1} \quad (3)$$

The number of covariance values depends on n number of dimensions in the dataset and that can be obtained by the following equation (4).

$$\mathrm{ncov}(n) = \frac{n!}{(n-2)! * 2} \quad (4)$$

As the dimension grows, the covariance values can be expressed in a covariance matrix that form as 3X3 matrix. This matrix can be generated for N attributes also, the below equation(5) shows the 3 X 3 covariance matrix.

$$c = \begin{pmatrix} \mathrm{cov}(A,A) & \mathrm{cov}(A,B) & \mathrm{cov}(A,C) \\ \mathrm{cov}(B,A) & \mathrm{cov}(B,B) & \mathrm{cov}(B,C) \\ \mathrm{cov}(C,A) & \mathrm{cov}(C,B) & \mathrm{cov}(C,C) \end{pmatrix} \quad (5)$$

Mean, standard deviation and covariance matrix are the fundamental metrics that can able to generate eigen vectors and eigen values. Consider M number of training gray scale images with size r x c i.e where r is considered as number of rows and c is considered as number of columns. This can be transformed into column vector which is considered as the first step for eigen value generation and also given in the equation (6). Thus the transformed images can be represented as $\Gamma_i$ , it is a column vector with dimension L x 1. Here L values are with the size of r x c.

$$\Gamma = (\Gamma_1, \ldots, \Gamma_m, \ldots, \Gamma_M) \quad (6)$$

The average of the face images of the data set is obtained by determining the mean from the collected data which is expressed in the equation (7).

$$\mu_\Gamma = \frac{1}{M}\sum_{m=1}^{M}\Gamma_m \quad (7)$$

The standard deviation is applied on the transformed images $\Gamma_m$ by subtracting the mean face value $\mu_\Gamma$ i.e differencing the equation (6) and (7) in order to obtain equation (8) which normalize the face vectors by removing the identical data and sustain the unique data of each image.

$$\tilde{\Gamma} = \Gamma - \mu_\Gamma \quad (8)$$

Reduced dimensionality of eigen vectors with size M x M instead of L x L is used to avoid the matrix size which are obtained by the covariance matrix that multiples $\tilde{\Gamma}^T$ with $\tilde{\Gamma}$ that is given in the equation (9).

$$cov = \frac{1}{M}\sum_{m=1}^{M}\tilde{\Gamma}_m^T\,\tilde{\Gamma}_m \quad (9)$$

The covariance matrix of the eigen faces of the equation (9) can be summarized as $A_{MXL}^T A_{LXM}$ and that gives $cov_{MXM}$ . The K number of eigen faces will be represented in the original dimensionality $U_k$ which can be obtained by the following equation (10) where the eigen value $v_k$ is used for matching the faces.

$$U_k = Av_k \quad (10)$$

In the training phase, the eigen vector $U_k$ is generated, the k dimensional vector $P_i$ for the $x_i$ input faces of M samples that is given in the equation (11) where i is ranged from one to M.

$$P_i = U_K^T(x_i - \mu_\Gamma) \quad (11)$$

Kernel function includes in various feature extractors and that converts low dimensional data into high dimensional data for producing better accuracy in the non-linear problems. Polynomial Kernel that is shown in the equation (12) is applied with PCA algorithm in order to improve the accuracy on face recognition process for having the dimensions d.

$$k(x_i, x_j) = (x_i^T x_j)^d \quad (12)$$

The eigen vectors are ordered on the basis of its importance for predicting in classification and the key single eigen vector is considered as facial feature which can individually works efficiently in KNN classification process.

### 3.2. FFT

Fast Fourier Transform is a transformation technique that converts spatial co-ordinates $f(x, y)$ of size M and N into frequency components $F(u, v)$ which is given in the equation (13). DC component, energy, Mean Absolute Value (MAV), energy and entropy are the four features which are attained from the frequency components of $(u, v)$ . MAV can be obtained by averaging the frequency transformed spatial image where frequency vectors are applied with absolute function in order to remove the negative values. Taking logarithm value of the frequency vectors and its frequency vectors are multiplied for evolving entropy feature from facial images.

$$F(u, v) = \frac{1}{N^2}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1} f(x, y)e^{-j2\Pi\left(\frac{ix}{M}+\frac{jy}{N}\right)} \quad (13)$$

The real and imaginary values of FFT vectors are summed to form an energy component that acts as an imperative feature in the proposed face recognition research work.

### 3.3.Haralickfeatures

The thirteen Haralick features [20] which are extracted from texture image classification are 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. Haralick et al. has extracted the above features from satellite images and classified as different classes using linear distinction function. The maximum accuracy achieved for the satellite images [20] in their research work was 83.5%. The nature and formulation of the Haralick features are also added in latha et al. research work [31].

### 3.4. SVM

Usage of support vectors and hyperplane [27] are started its journey from 1960s and the first paper was presented in 1992 by Vladimir Vapnik and colleagues. In non-linear mapping, SVM maps dataset from its original dimension to higher dimension and that gives high accuracy by fitting best hyperplane in the dataset, for having instance 3-D input vector transformed into 6-D vectors. Kernel functions are added with SVM for non-linear mapping process which are replaced by the over-buget dot operator and produce good results in accuracy calculation. Polynomial kernel,

Gaussian radial basis function kernel and Sigmoid are well known kernels which are added with specific feature extractors or classifiers in order to enhance the recognition accuracy.
Polynomial kernel of degree h normalizes the input dataset and that is defined in the equation (14) where $X_i$ and $X_j$ are the input vectors.

$$K(X_i, X_j) = (X_i . X_j + 1)^h \quad (14)$$

Gaussian radial basis function kernel is based on the RBF (Radial Basis Function) neural network to fix the hyperplane in the dataset which can be obtained by the following equation(15). The σ value will be automatically or manually adjusted according to the nature of the dataset and that value must be greater than zero.

$$K(X_i, X_j) = e^{-\|x_i - x_j\|^2 / 2\sigma^2} \quad (15)$$

Sigmoid kernel uses multilayer perceptron technique of Neural Networks and that has no hidden layers and also have less computations which is generated using below equation(16). $\kappa$is the parameter which is calculated with the following equation(17) by using σ.

$$K(X_i, X_j) = tanh(\kappa X_i . X_j - \delta) \quad (16)$$

$$\kappa = \frac{1}{2\sigma^2} \quad (17)$$

Multi classifiers [26] are involved for multi-classes problem that is, when there is an M classes problem M classifiers are modeled. This approach is termed as one versus all. In each case, one class is true and other all classes are false.

### 3.5. K-nearest-neighbour classifiers

In KNN, closeness between the tuples with set of features are calculated using distance metrics like Euclidean distance, Manhattan distance, Minkowski etc. K denotes the number of nearest neighbours which are close to the testing tuple. In the proposed work, Euclidean distance measurement acquire for n number of features by the following equation (18), the tuples $T_1$ and $T_2$ are having the following features $t_{11}, t_{12}, t_{13}, \ldots, t_{1n}$ features are in $T_1$ and $t_{21}, t_{22}, t_{23}, \ldots, t_{2n}$ for features are in $T_2$.

$$d(T_1, T_2) = \sqrt{\sum_{i=1}^{n} (t_{1i} - t_{2i})^2} \quad (18)$$

## 4. Experiment and result

Features extraction, feature selection and classification are the three phases of FRS that can be done systematically in order to achieve high accuracy of recognition rate. In the proposed research work, the first two phases are effectively carried out with Mathlab 2015, by forming a feature space with ORL database [22][28]. The features PCA, KPCA, FFT and Haralick are mapped with class labels which vary from person one to forty. The 400 samples of 40 individuals are collected and analyzed with two different classification methods [27] such as KNN and SVM using IBM SPSS Predictive Modeler.
In the feature space, features are added (forward selection) or pruned (backward selection) using hybrid feature selection process with respect to the accuracy [27] evolved with the classifiers like SVM and KNN.

### 4.1. Diverse data set

The features are extracted by the methodologies FFT, Haralick and KPCA are clustered in to subsets as FFT set, HARA set, FHA set (FFT set + HARA set) and FHAKP (FFT set + HARA set + SVPC).
The first feature set FFT (Fast Fourier Transform) is formed by applying statistical measures such as energy, entropy and mean on the frequency vectors of FFT. HARA feature set is the second feature set which performs thirteen statistical metrics on the face images and the third feature set FHA is formed by merging the first two feature sets (FFT set and HARA set). The traditional PCA vectors are transformed in to high dimensional feature space by the polynomial kernel to project the data in to certain ranges that can be assessed and accessed effectively. A Single Vital Principal Component (SVPC) is obtained from the transformed PCA (Principal Component Analysis) eigen vectors by sorting the vectors on prioritizing its worthiness. SVPC feature along with FHA data set forms the fourth data set FHAKP. SVPC is analyzedindividually which shows higher accuracy for KNN classifier with less space complexity and works efficiently with SVM classifier.

### 4.2.Analyzing diverse data set with KRBF_SVM, KPOLY_SVM and KSIG_SVM

In the proposed work, data set is partitioned as 50% for training and 50% testing process. Thus, the accuracy of the model is recorded for both training and testing phases with different feature set by using SVM classifier. Accuracy is measured by the number of records correctly predicted with respect to its class.
SVM with kernel RBF (KRBF_SVM) are analyzed for the proposed feature set with various gamma values. In order to fine-tune the model, the experiment is carried out with different gamma values until no more further improvement in the accuracy which is recorded in table1 and illustrated in the figure1.
Among all the feature sets, FHAKP SET shows the best results with Polynomial kernel SVM (KPOLY_SVM) and produce accuracy up to 98.04% for gamma value 1 that are shown in the table2. Accuracy is stagnated for further increase or decrease of gamma value and the observations are depicted in figure2.
SVM accuracy with sigmoidal kernel (KSIG_SVM) for the dataset is fair accuracy of up to 63.9% with gamma value 0.05 which is shown from the table3 and figure3. On further adjusting the gamma value, the accuracy remains firm. SVPC feature individually with SVM gives poor accuracy i.e. below 40% for gamma value ranges from 0.01 to 90 but shows tremendous rise in the accuracy level up to 80% with gamma value 102 which is not appreciable. So, it is experimentally found that SVPC feature does not perform well with SVM classifier. The four feature sets works fine with KRBF_SVM than with KPOLY_SVM and KSIG_SVM.

**Table 1**: Analyzing Diverse Data Set with KRBF_SVM

| Facial Feature set | Accuracy in Percentage | | | | | |
|---|---|---|---|---|---|---|
| | Training with KRBF_SVM Gamma=2 | Testing with KRBF_SVM Gamma=2 | Training with KRBF_SVM Gamma=3 | Testing with KRBF_SVM Gamma=3 | Training with KRBF_SVM Gamma=4 | Testing with KRBF_SVM Gamma=4 |
| FFT SET | 63.08% | 65.37% | 62.05% | 67.80% | 64.10% | 75.12% |
| HARA SET | 95.90% | 95.51% | 97.44% | 98.54% | 98.46% | 99.51% |
| FHA SET | 97.95% | 99.02% | 99.49% | 99.02% | 99.49% | 99.51% |
| FHAKP SET | 98.46% | 99.02% | 99.49% | 99.02% | 99.49% | 99.51% |

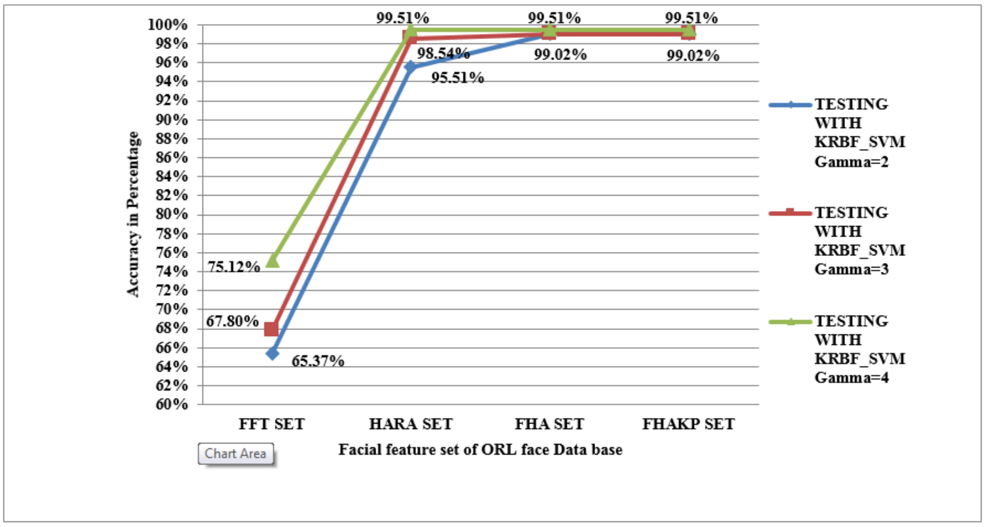


**Fig. 1:** Analyzing Diverse Data Set with KRBF_SVM.

**Table 2:** AnalyzingDiverse Data Setwith KPOLY_SVM

| Facial features set | Training with KPOLY_SVM Gamma=1 | Testing with KPOLY_SVM Gamma=1 |
|---|---|---|
| FFT SET | 54.87% | 59.51% |
| HARA SET | 94.36% | 95.61% |
| FHA SET | 96.92% | 98.05% |
| FHAKP SET | 97.44% | 98.04% |

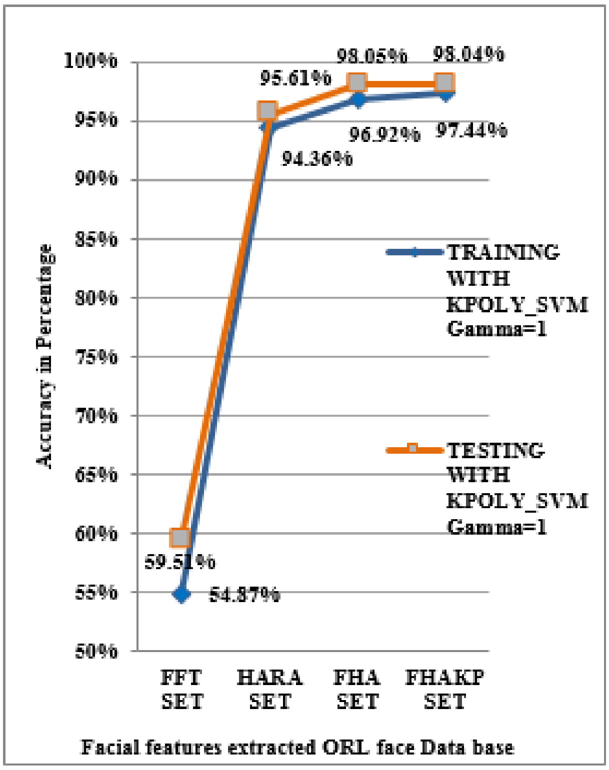


**Fig. 2:** Analyzing Diverse Data Set with KPOLY_SVM.

**Table 3:** Analyzing Diverse Data Set with KSIG_SVM

| Facial features extracted ORL face Data base | Training with KSIG_SVM Gamma=0.05 | Testing with KSIG_SVM Gamma=0.05 |
|---|---|---|
| FFT SET | 33.33% | 35.61% |
| HARA SET | 63.08% | 60.00% |
| FHA SET | 63.08% | 63.90% |
| FHAKP SET | 63.08% | 63.90% |

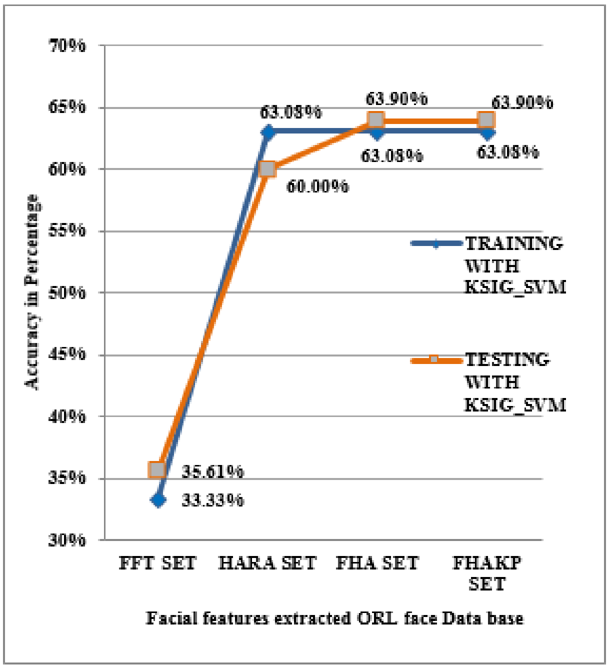


**Fig. 3:** Analyzing Diverse Data Set with Ksig_SVM.

## 4.3.Analysing diverse data set with KNN

Nearest neighbour rule is a template matching technique which is in need of more space since all the records are kept in the feature space as a training model. The Euclidean distance for testing tuple with respect to the other tuples is measured where all the records are involved in the matching process.

In some instances, the nearest neighbour may be the testing tuple itself, this leads to uncertainty in accuracy level when performance is measured. This can be avoided by considering neighbours as three or greater than higher value. However in this reseach work, matching is done with all the records except the query record. The first close tuple is considered as matched tuple i.e k=1 which produce 100% of accuracy with all the proposed datasets.

The figure4 generated by IBM SPSS predictive modeler tool for FHA set, depicts the matching process for the query record number six and the distances are recorded in table4. The test record is correctly matched with 1 to 10 records of its class. In the sample case shown in the below table, the nearest neighbours for the sixth tuple are second, third and seventh tuple which is the genuine matching so it produces true positive result. The nearest neighbours of the test record 6 are exposed by using important predictors and it is shown in the figure4.

**Table 4:**K NearestNeighboursand Distances for FHA Set of Test Record 6

| Test Record | Nearest Neighbours | | | Nearest Distances | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 1 | 2 | 3 |
| 6 | 2 | 3 | 7 | 0.578 | 1.23 | 1.273 |

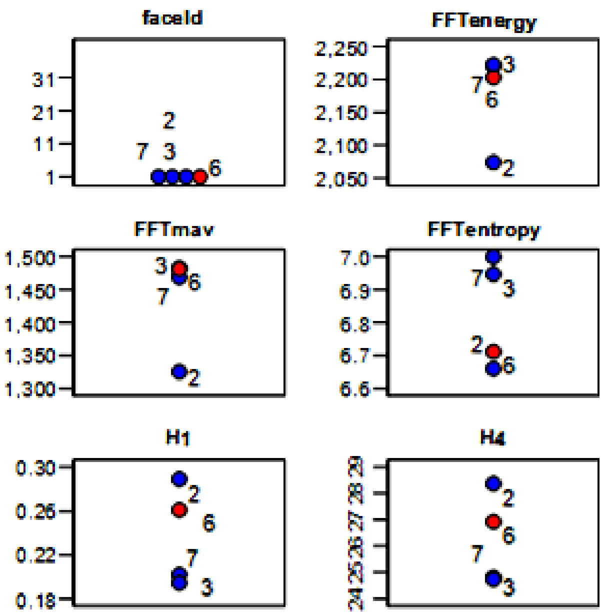


**Fig. 4:**K nearestNeighboursand Distances for FHA Set of Test Record 6.

The figure 5 and figure 6 shows the 3-D predictor space of selected predictors of FHA set where focal record six is associated with three neighbours(k=3) and also associated with a Single neighbour(k=1). Similarly predictor space can be generated with other predictors model and feature sets. Tracing of best k value can be done by analyzing the error rate in the training model which is shown in the figure 7.

Ezoji et al. in their research work [25] concluded that, as k increases, the accuracy of the face recognition process also increases. In the proposed research work, accuracy increases when the number of neighbours of k decreases. Results of three nearest neighbours (k=3) and one nearest neighbour (k=1), are compared for the entire feature set which is recorded and shown in the table 5.

The growth of accuracy from FFT set to the single feature set SVPC is illustrated in figure 8. In this research work, a single component of PCA (SVPC) becomes a dominant predictor with KNN classifier with the accuracy of 97.5% for three nearest neighbours and 100% of accuracy for one nearest neighbour. Shih-Ming Huang et al [16], applied some of principal components techniques for other components, that occupies the feature space in order to improve the performance of the FRS.

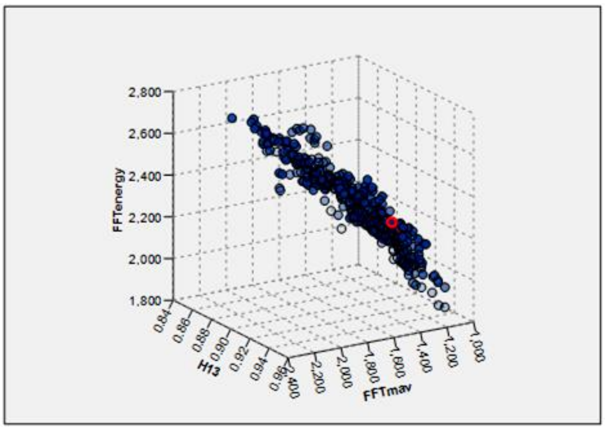


**Fig. 5:** Predictor Space of Selected Predictors for FHA Set Where K=3.

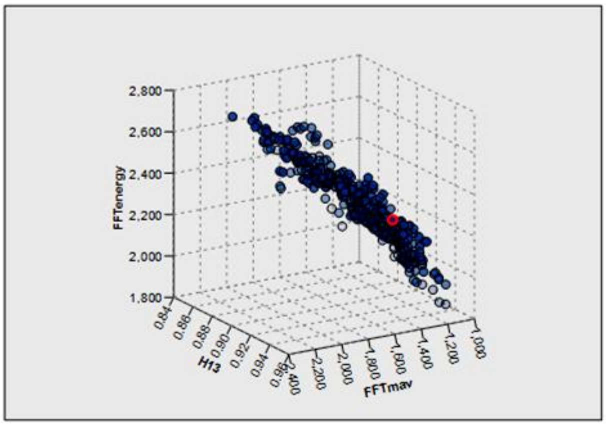


**Fig. 6:** Predictor Space of Selected Predictors for FHA Set Where K=[1].

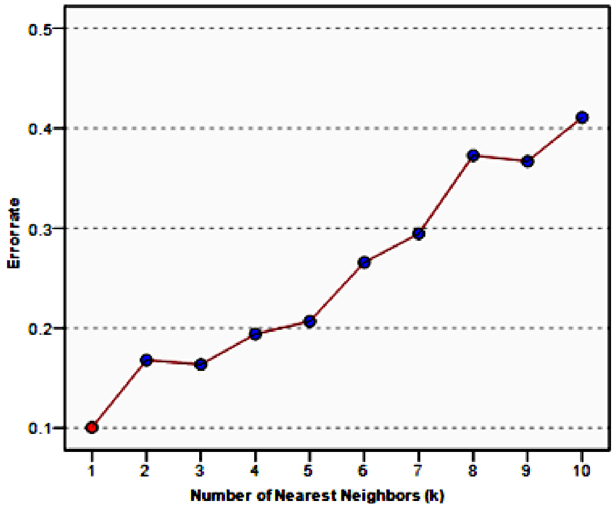


**Fig. 7:**Number of Neighbours vs.Error Rate.

**Table 6:**Accuracy for Diverse Features with KNN Classifier

| Facial features extracted ORL face Data base | Accuracy With KNN_5 or 10 FOLDS K=3 | Accuracy With KNN_5 / 10 FOLDS K=1 |
|---|---|---|
| FFT SET | 82.75% | 100% |
| HARA SET | 92.50% | 100% |
| FHA SET | 93.25% | 100% |
| FHAKP SET | 93.25% | 100% |
| SVPC | 97.50% | 100% |

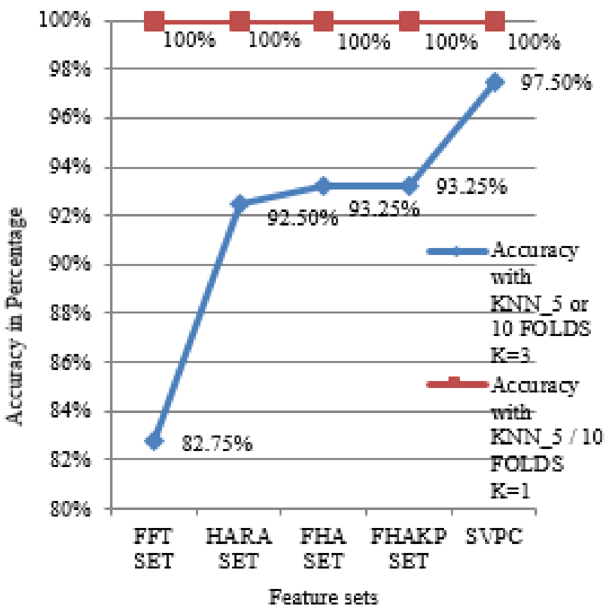


**Fig. 8:**Accuracy for Diverse Features with KNN Classifier.

## 5. Conclusion

The four feature sets FFT set, HARA set, FHA set, FHAKP set and the individual feature SVPC are created from KPCA, FFT and Haralick methodologies using ORL face data base. These are familiar and known techniques in the field of face recognition where novel techniques are convolved to form a dominant feature set. When compared with all the three approaches of SVM with three different kernels, RBF scored higher accuracy than the other two kernels and its accuracy level is 99.54%. KNN classifier has scored 100% matching with all the proposed feature sets for having single nearest neighbour which can be accepted since it excludes the recording query during the matching process. Analysing and identifying the efficient feature vectors for building a reliable face recognition system gives a hope of moving in to the world of digitalization which is safe and comfortable for human survival.

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