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Face Recognition Using Hybrid Feature Space in Conjunction with Support Vector Machine

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ABSTRACT

Face recognition is one of the challenging problems in the area of pattern detection and recognition. It is practically applicable in different automated systems for security purpose, access control, public security, desktop login and many more. Due to vagueness and intricacy in face pattern, there need more exercise in order to enhance the quality of face recognition. For this purpose, we propose a robust and reliable computational model for face recognition. In this model, two Transformation methods such as discrete wavelet transform (DWT) and discrete sine transform (DST) along with local based feature representation namely: local binary pattern (LBP) and local phase quantization are used to extract numerical features from face images. Irrelevant, noisy, and redundant features are eradicated using Minimum redundancy maximum relevance (mRMR). Various classification learners such as K-nearest neighbor (KNN), Support vector machine (SVM) and Probabilistic Neural Network (PNN) are utilized. SUMS facial dataset and 10-folds cross validation test are used to evaluate the performance of classification algorithms. Our proposed model achieved quite promising performance, which is 92.1% accuracy. This achievement is ascribed with the discrimination power of hybrid space and SVM. It is anticipated that the proposed computational model might be helpful for academia and researchers in face detection and recognition.
KEYWORDS: *DST, DWT, LBP, LPQ, KNN, SVM, PNN.*

1. INTRODUCTION

In order to develop an efficient and reliable recognition system a lots of efforts have been carried out by the researchers for face detection [1; 2; 3] and individual identification [4]. Face recognition is one of the few biometric methods that possess the merits of both high accuracy and low intrusiveness. It's used in many areas such as entertainment, information security and surveillance [5].Hoang Le et al., used two dimensional principal component analysis approach to extract features from both FERET and AT&T facial datasets. The recognition rate of the proposed system is evaluated through SVM and KNN [6]. Chengjun et al., proposed Gabor–Fisher classifier (GFC) for face recognition. Augmented Gabor based features vector is derived through the Gabor wavelet representation of the face images. In order to get high discriminative features, the extracted features space is reduced using Enhanced Fisher linear Discriminant Model (EFM).The comparative analysis of the GFC with all the considerable techniques reveals that proposed GFC achieved the high recognition results using FERAT frontal faces images [7].similarly, Yilmaz et al., applied a novel preprocessing technique "Eigen Hills". In this approach Eigen face based features is extracted from facial images, but the performance results did not achieved the expected results due to expression variation [8; 9]. Furthermore, Jagadeesh et al., has proposed "DBC-FR" algorithm for face recognition. Proposed technique is tested on NIR face image database. In order to match the extracted features, Euclidian distance is utilized for training and testing purpose. It is observed that proposed method obtained better success rates than existing techniques [10]. Likely, Nayak et al., used fused discrete cosine transform and discrete wavelet transform to extract feature spaces from ORL database. The performance of the proposed system is measured using SVM and ANN [11]. Wadkar et al., applied haar wavelet transform and Biorthogonal wavelet transform based techniques on ORL facial dataset. The comparative analysis of the proposed shows that haar wavelet transform obtained better results than that of biorthogonal wavelet transform [12]. Hengliang et al., used HOG filter on the normalized images. Both local and global HOG features are extracted by combining Principal component analysis and linear discriminant analysis [13]. Moreover, local based feature based approaches received the attention of the researchers for facial detection from last few years [14]. LBP is a non-parametric technique that assembles efficient information about local structure of face image and recognizes an individual based on gather features [15; 16]. Ahonen et al., divided the face image into several region. High discriminative descriptors are extracted from each sub parts of the image and concatenated into a single feature vector. The recognition rate is evaluated using nearest neighbor classifier. The proposed scheme clearly shows the superiority over all the compared methods [17].

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In this work, we proposed a robust and intelligent computational model for face recognition. In order to extract the reliable features we utilized four different nature schemes such as DWT, DST, LBP and LPQ. Furthermore, SVM, PNN and KNN are used as classification learners.

The rest of the paper is organized as follows: Materials and Methods are represented in Section 2. Section 3 represents Results and discussion and finally conclusions are drawn in the last Section.

2. MATERIALS AND METHODS

In this section, we discuss the feature extraction, selection and classification algorithms used in proposed approach.

2.1) Datasets Description:

In order to develop a computational model, a benchmark dataset is always required to train the model. In this work, we have used the Stanford university medical students (SUMS) facial dataset for gender classification [46]. *SUMS* contain 400 face images having 200*200 pixels. Dataset is equally labeled in 200, 200 images of both male and female. All the images are stored in JPEG format. A sample is as follows:

Figure 1. Sample images of SUMS Database

2.2) Discrete wavelet Transform (DWT):

Wavelet transform is one of the most increasingly popular tools for image processing it has been used in many applications for recognition, detection and compression purpose. The key reason for choosing wavelet transform is its complete theoretical skeleton, high flexibility and low computational complexity [18; 19]. The main advantage of wavelet over other transformation methods is that its temporal resolution, because it computes both frequency and location information [18].

Two dimensional wavelet transform of an image is given by equation (1)

$$DWT(j,k) = \frac{1}{\sqrt{2^j}} \int_{-\infty}^{+\infty} f(x)\psi(\frac{x}{2} - k)dx \qquad (1)$$

where j is the power of binary scaling and *k* is a constant of the filter.

Wavelet transform first calculates 1-D DWT on the rows and then 1-D DWT on the columns. For 2D Wavelet transform the image is decomposed into 4 sub parts, which are Low-Low (LL), High-Low (HL), Low-High (LH), High-High (HH).

In this paper, we have used discrete wavelet transform to decompose face images up to 2 levels. In order to extract features, we have used several statistics measures such as Max, Energy, standard deviation, Kurtosis, Euclidian distance, skewness and variance to extract features.

2.3) Discrete Sine transform (DST)

DST is a kind of Sinusoidal unitary and separable Transform developed by Jain [21]. Fundamental properties of DST are such as scaling, shifting, data compression and convolution have been applied in various applications [22]. DST is the sum of sine transform functions, whose spectral methods are utilized for numerical solution of various partial differential equations. DST algorithm works on only finite discrete sequences. DST is computationally efficient and fast transformation algorithm that produces the real and orthogonal matrix [23,45]. DST matrix is formed by arranging the pixels in row wise [24]. In this work, skewness, kurtosis, max, standard deviation and variance are utilized as attributes to extract robust and reliable features using DST.

2.4) Local Binary Pattern (LBP)

LBP has widely been used by the researcher for Facial Analysis, Image processing, Texture Analysis, and etc. The pioneer work on the Local binary pattern operator was done by Ojala [25]. *LBP* is a non parametric Feature extraction method that assembles local special structure of an image [26]. Computational simplicity and invariance against monotonic illumination changes are the important properties of LBP. The function of *LBP* operator is depicted in figure 2. *LBP* labels

the pixel of a face images. Each of pixels is compare with its center value of 3*3 surrounding neighbors and obtained a binary number by concatenating all the binary values in clockwise direction [27].

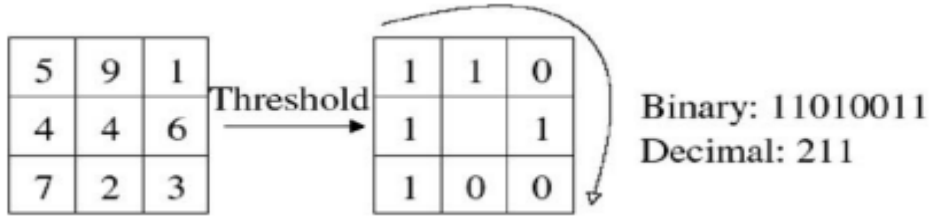

Figure 2. The basic LBP operator [20]

LBP histograms are extracted from each sub region of the image and then concatenated into a single feature vector [28, 29]. Histogram of an image $f_l(x, y)$ can be represented as:

$$H_{i,j} = \sum_{x,y} I(f_l(x, y) = i) \quad (2)$$

2.5) Local Phase Quantization (LPQ)

LPQ is the robust and efficient local features based algorithm. LPQ was proposed by Ojansivu and Heikkil for texture description [30]. LPQ operator divides the label image into non-overlapping rectangular regions of equal size. Each sub region of an image is computed independently to extract useful local information. LPQ computes the local phase of an N*N image by applying Short-term Fourier transform algorithm, illustrated in equation (3).For every pixel *x*, STFT computes the local coefficients in the local neighborhood *Nx* as follows:

$$F(u, X) = \sum_{y} f(y)\omega R(y - x)e^{-j2\pi u^T y} \quad (3)$$

STFT calculates Local Fourier coefficient against each pixel of an image. Phase information is obtained by the quantization of each coefficient using binary scalar quantizer. At last the resultant eight bit binary coefficients are represented using binary coding [31; 32].

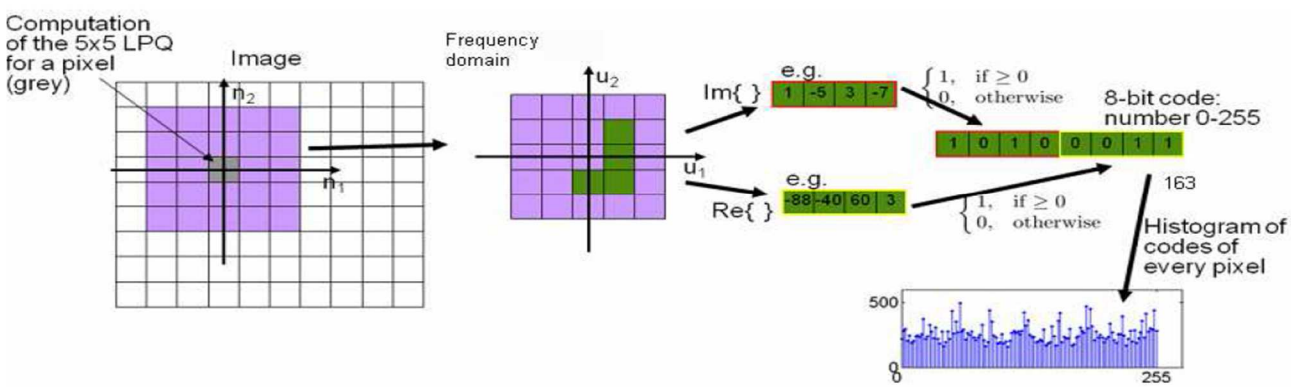

Figure 3. Local Phase Quantization Algorithm

2.6) Minimum Redundancy Maximum Relevance (mRMR)

mRMR is mutual information based dimensionality reduction technique that find out feature subspace that are mutually dissimilar, contains less number of redundancy with other features that construct the feature vector to attain improved results and maximum relevance towards the target class[33]. Statistical properties such relevance and correlation between can calculated using mutual information [34]. The mutual information (*I*) of two features x,y can be defined as:

$$I(x, y) = \sum_{i,j} p(x_i, y_j) \log \frac{p(x_i, y_j)}{p(x_i)p(y_j)} \quad (4)$$

$P(x_i, y_j)$ Calculates the joint joint probabilistic distribution and $p(x_i)$, $p(y_i)$ are the marginal probabilistic .
Minimum redundancy (*mR*) among the features can be found as:

$$mR = \frac{1}{|s|^2} \sum_{x,y \in S} I(x, y) \quad (5)$$

Where S represents the feature vector and |S| are the total number of features in S.
Similarly, maximum relevance (MR) condition used to maximize the relevance of all features of "S" and target classification variable.

$$MR = \frac{1}{|s|} \sum_{x \in S} I(x, z) \quad (6)$$

After calculating minimum redundancy and maximum relevance, finally both of the conditions are combined to obtain a single feature subspace as follows:

$$\max(MR/mR) \quad (7)$$

2.7) K-nearest neighbor algorithm (Knn)

K-Nearest Neighbor algorithm is one of the most popular classifier in the area of pattern recognition and image processing. KNN is a non-parametric classification and has no prior knowledge about the distribution of the data [19; 35]. Owing to its simplicity and good performance results, we use KNN for classifying objects based on closest training examples in the feature vector. For each test image, it calculates Euclidean Distance between the closest members of the training data set. The Euclidean distance formula is given in equation (8):

$$d(x, y) = \sqrt{\sum_{i=1}^{N} (x_i - y_i)^2} \quad (8)$$

2.8) Support Vector Machine (SVM)

SVM is a very powerful statistical learning method that has been extensively applied by the researcher in the area of image processing and machine learning. SVM is a kind of supervised learning in which class labels of the training data is already known. SVM draw a parallel line to classify the data of different classes [36; 37; 38]. SVM are utilized for both binary and multi class problems. SVM have the unique property of Structural Risk minimization principal that build the classifier computational better than other [39; 40]. SVM utilizes various types of kernel including linear, polynomial and radial basis kernel function [41; 42]. In our case polynomial kernel is utilized to achieve satisfactory results.

2.9) Probabilistic Neural Network (PNN)

Probabilistic neural network (PNN) is most dominant machine learning tool that can evaluate the performance based on conventional statistical Bayesian decision rule classification algorithm introduced by specht in 1990 [132; 133]. PNN is a kind of supervised learning that calculates the probability of the instances of a specific class [134]. Owing the simplicity, fast training and transparency made PNN one of the most optimal classification learner. [135]. The complete framework of PNN consist of four layers shown in the figure.3. The input layer computes the distance from the input vector to the training input vector. The second layer evaluates the summation by the contribution of input from each class and then finally output layer categorize the test examples into the predefined classes having maximum probability [137].

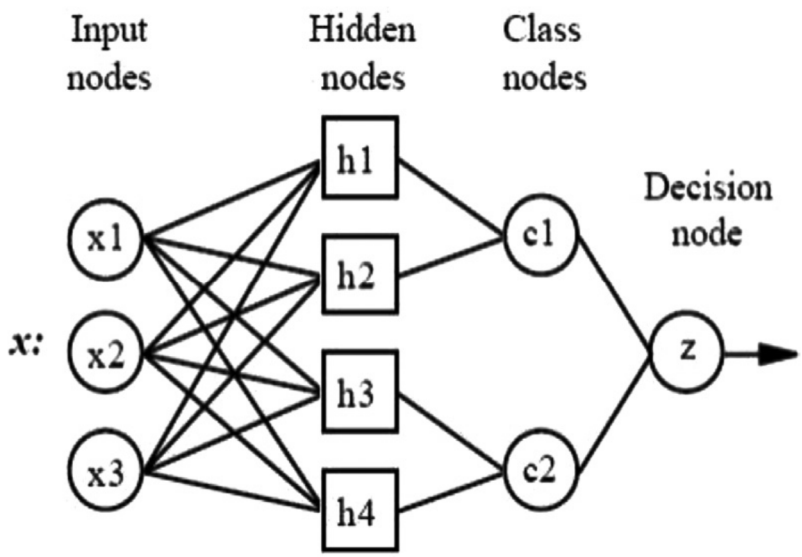

Figure 4. Structure of PNN

The input layer have *N* number of nodes, each node in this layer is utilized as an independent variable. Input layer is associated with M nodes of the pattern layer. Each input vector P_i in pattern layer is processed by activation function.

$$Z_{ij} = \exp\left(-\left|\left|P_j - P_i\right|\right|^2\right)/\delta^2\ ) \quad (9)$$

where Zij represents the output of pattern node *j* and δ is a smoothing factor that adjust the activation function.

Pj – Pi calculate the distance of the input vector *Pi* and the vector *Pj* of the pattern node *j*. if the distance between *Pi* and *Pj* increases then similarity among the feature vector will decreases. Summation layer takes the input after calculating pattern layer. Summation layer contains *v* competitive nodes, each corresponding to one class.

For an input vector *Pi*, the summation node *k* receives the outputs of the associated pattern nodes for producing an output:

$$f_v(P_i) = \frac{1}{N_v \sum_{\forall P_i \in Q_v} \exp\ [\left(P_j {P_i}^T - 1\right)/\delta^2\ )]} \quad (10)$$

Where *Qv* denoted the label of the class corresponding to the summation node *v*, while *Nv* is the number of training objects belonging to this class.

The outputs of the summation layer can be calculated using posterior class probabilities:

$$P(Q_i = V|P_i) = \frac{f_V(P_i)}{\sum_{v=1}^{V} f_V\ (P_i)} \quad (11)$$

2.10) Proposed Method

Looking at the importance of face recognition in the field of bioinformatics and pattern recognition, we propose a robust, efficient, and accurate model for face identification. In this model, features are extracted features from SUMS dataset using both local and transformation techniques, DST and DWT are utilized as transform approaches and local features are obtained by applying LBP and LPQ. Furthermore extracted feature vectors of DST and DWT are combined together to obtain a high predictive features set of the face image. Finally, mRMR is utilized to select high descriptive information from extracted feature set. In order to measure the prediction rate of the proposed approach, K-Nearest Neighbor, Support Vector Machine and Probabilistic Neural Network are utilized as classification algorithms. Block diagram of the proposed system is depicted in figure 5. Different performance measures are used for assessing the performance of classification algorithm, which are mention below.

$$\text{Accuracy} = \sum_{i=1}^{k} \frac{\text{TPi}}{\text{N}} \quad (12)$$

$$\text{Sensitivity} = \left(\frac{\text{TP}}{\text{TP}} + \text{FN}\right) * 100 \quad (13)$$

$$\text{Specificity} = \left(\frac{\text{TN}}{\text{FP}} + \text{FN}\right) * 100 \quad (14)$$

$$\text{MCC} = \frac{(\text{TP}*\text{TN} - \text{FP}*\text{FN})}{\sqrt{([\text{TP}+\text{FP}][\text{TP}+\text{FN}][\text{TN}+\text{FP}][\text{TN}+\text{FN}])}} \quad (15)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (16)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (17)$$

$$\text{F} - \text{measure} = 2 * \left(\frac{\text{Presion*Recall}}{\text{Presion+Recall}}\right) \quad (18)$$

Where TP, FN, TN, and FP represents the number of True Positive, False negative, True Negative and False Positive, respectively.

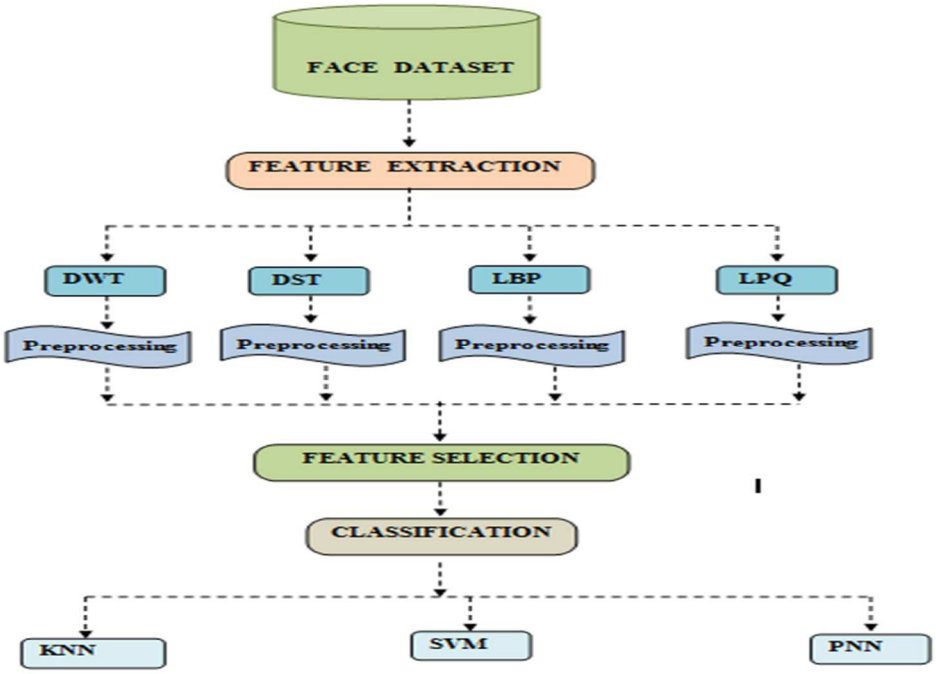

Figure 5. Proposed model for Gender Classification

3. RESULTS AND DISCUSSION

In this paper, we have analyzed the performance of several classification algorithms using different feature space of DST, DWT, LBP and LPQ. The empirical results of various classification algorithms are discussed below:

3.1) Prediction performance using Transform based feature Vectors

The prediction rate of the classification algorithms in conjunction with Transform based feature vectors are listed in Table.1.In this work we utilized two transformation approaches such as DWT and DST to extract the Valuable feature from SUMS face dataset. In order to reduce dimensionality and minimize the redundancy of the extracted feature vectors mRMR technique is applied. The performance results of the proposed system are evaluated before the feature selection technique as well as after. In case of KNN, DWT feature set obtained an accuracy of 89% with sensitivity of 94.5%, specificity of 96%, MCC of 0.76 and F-measure of 0.89. The performance rate of SVM using DWT is 88.8% accuracy, 89.5% sensitivity, 88% specificity 0.77% MCC and 0.89 F-measure. Similarly, PNN has obtained 60.1% accuracy with sensitivity, specificity, MCC and F-measure of 62.5%, 56%, 0.17 and 0.61, respectively. Likely, DST based feature vector are also listed Table.1. In case of KNN, DST feature vector reported the accuracy of 90.7 % with 95% sensitivity, 86.5% specificity, 0.82 MCC and 0.91 F-measure. In contrast, SVM achieved 90% accuracy with sensitivity, specificity, MCC and F-measure of 92 %, 88 %, 0.80 and 0.90 respectively. Similarly, DST feature vector is further evaluated with PNN and obtained the success rate of 90.1%, sensitivity of 93.7 %, specificity of 86 %, MCC of 0.82 and F-measure of 0.91.

3.2) Prediction performance using Local based feature Vectors

In this work, we used two different local feature approaches such as LBP and LPQ to extract the information from face images. In order to obtain highly reliable information and reduce dimensionality of the feature vector mRMR is utilized. The performance results classification learners using LPQ and LBP feature vectors are shown in Table 2. In case of LBP, the highest accuracy of 89.5% achieved using SVM having sensitivity of 92%, specificity of 87%, MCC of 0.79,

and F-measure of 0.89. On other hand KNN obtained the success rate of 86%, sensitivity, specificity, MCC and F-measure of 94%, 79.5%, 0.74 and 0.87, respectively. The predicted results of PNN are 85.8% accuracy, 83% sensitivity, 78.5% specificity, 0.72 MCC and 0.87 F-measure. Similarly LPQ feature vector is also measured by proposed classification learners given in Table 2. Using LPQ feature space the highest prediction rate obtained is 88.2% using KNN with 95.5% sensitivity, 80.5% specificity, 0.77 MCC and 0.89 F-measure. Likewise, PNN has yielded an accuracy of 89% with sensitivity, specificity, MCC, F-measure of 93%, 77%, 0.71 and 0.86, respectively. Finally, SVM achieved an accuracy of 58.8% that is comparatively lower than other utilized classification algorithms.

Table 1. Success rate of classifier using transform based approaches

	LBP					***LPQ***				
Methods	**Acc%**	**Sen %**	**Spe%**	**MCC**	**F-M**	**Acc%**	**Sen %**	**Spe%**	**MCC**	**F-M**
KNN	***86***	***94***	***79.5***	***0.74***	***0.87***	88.2	95.5	80.5	0.77	0.89
SVM	89.5	92	87	0.79	0.89	58.8	48	68	0.16	0.53
PNN	85.8	93	78.5	0.72	0.87	*87*	*93*	*77*	*0.71*	*0.86*

Table 2. Success rate of classifier using Local based approaches

	DWT					***DST***				
Methods	**Acc%**	**Sen %**	**Spe%**	**MCC**	**F-M**	**Acc%**	**Sen %**	**Spe%**	**MCC**	**F-M**
KNN	***89***	***94.5***	***96***	***0.76***	***0.89***	90.7	95	86.5	0.82	0.91
SVM	88.8	89.5	88	0.77	0.89	90	92	88	0.80	0.90
PNN	60.1	62.5	56	0.17	0.61	***90.1***	***93.7***	***86***	***0.8***	***0.91***

3.3) Prediction performance using Hybrid feature Vector

In order to enhance the performance rate of the proposed system we used Hybrid approach. In case of Hybrid approach, both DWT and DST based feature spaces are concatenated to form a single feature space. The performance results of Hybrid feature vector are given in Table 3.The prediction accuracy using KNN is 91% with 87% sensitivity, 95% specificity, 0.82 MCC and 0.91 F-measure. While applying SVM, the highest success rate of 92.3% is achieved with sensitivity, specificity, MCC and F-measure of 93.5%, 90%, 0.82 and 0.91, respectively. On other hand PNN obtained 57% of accuracy.

3.4) Comparison analysis of the proposed system with existing approaches

A number of efforts have been carried out by the researchers for gender classification. In order to compare the performance of our proposed model with already existing methods a comparison has been drawn in Table 4 using SUMS facial dataset. The comparison of proposed model and already existing approaches has been drawn in Table 4. Rai et; al [43] proposed a computational model for gender classification using DCT feature extraction scheme and achieved 88% accuracy. Similarly, the proposed system of sun *et al.*, [44] has yielded an accuracy of 91.3%. In contrast, our proposed model has achieved 92.1% accuracy, which better than already existing approach.

Table 3. Success rate of classifier using Hybrid approach

Methods	**DWT +DST**				
	Acc%	**Sen%**	**Spe%**	**MCC**	**F-M**
KNN	91	87	95	0.82	0.91
SVM	92.1	93.5	89	0.82	0.91
PNN	57	58.5	55.5	0.14	0.58

Table 4. Performance Comparison with Existing techniques

Methods	**Performance Rate**
Rai et. al[43]	88%
Sun et. al[44]	91.3%
Proposed Method	92.1%

Conclusions

In this work, a quite promising automated prediction system for Gender classification using facial images is proposed. In order to investigate the performance of proposed model both the transformation and local pattern based approaches are used to extract features from SUMS dataset. Various classification algorithms namely: KNN, SVM and PNN are utilized as classification algorithms. The performance of the classification learners are assessed using 10 folds cross validation.

Hybrid feature vector of DWT and DST achieved the highest accuracy of 92.1% using SVM. It is anticipated that the proposed computational model might be helpful for academia and researchers in face detection and recognition.

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