Robust Illumination and Pose Invariant Face Recognition System using Support Vector Machines

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Abstract: The fundamental objective behind the denoising is to get rid of the noise while recollecting the significant signal features to the maximum possible extent. This issue seems to be very simple against the backdrop of realistic scenarios, where the category and quantity of noise, along with the noise and the kind of images all are variable parameters, and a solitary technique or approach is incompetent to yield reasonable results. There is a host of methods employed to eliminate the noise in images and carry out the classification procedure efficiently. In the innovative approach, at the outset, the images are shortlisted from the database, and thereafter the technique flows through the following three phases such as the pre-processing procedure, feature extraction procedure and the classification procedure by means of the Support Vector Machine (SVM). In the feature extraction procedure the Gray Level Co-occurrence Matrix (GLCM) traits like the autocorrelation, contrast, cluster prominence, cluster shade, dissimilarity, energy, area, homogeneity, perimeter, circularity and entropy are extracted. Subsequently, SVM is employed for the purpose of the face recognition, because the optimal separating hyper plane can be achieved easily after ascertaining the thinner product between feature vectors, which constitutes an exemplary quality of the SVM. The kernel functions are able to achieve only the inner product value in the feature space being unaware of the nonlinear mapping.

Keywords: GLCM Features, Face recognition, Nonlinear function, Support Vector Machines.

INTRODUCTION

With several innovative biometric techniques like the fingerprint, iris, palm, gait and so on, the face detection method have become one of the most exciting domains till date [1]. The face is one of the most frequently employed organs used by human being to detect one other. Right from its growth, the human brain has built up superbly specialized regions devoted to the examination of the facial images. In the past decades, face recognition has emerged as a synergetic investigation zone with the launch of several kinds of innovative algorithms and methods intended to be identical the amazing skills of the human brain [2]. The everyday task of face detection on its users is one of the causes for the ever zooming enthusiasm created by it among the investigating community as a whole during the past several decades. This has paved the way for the design and launch of several face recognition methods such as the homogeneous lighting and permanent frontal poses which is able to achieve amazing and consistent efficiency in execution [3].

The face recognition has emerged as one of the most dynamic investigation domains in the pattern recognition. It plays a significant role in several application regions like the human machine interface, validation and inspection [4]. The concurrent automatic face recognition techniques are faced with a multitude of sources of within-class distinction such as the pose, expression, and illumination, in addition to the occlusion or disguise. From times immemorial, intensive investigation by experimenters dedicated to the pattern recognition have yielded good results in starting several novel techniques intended for the successful addressing of the relative factors independently [5]. At present, it is...
common knowledge that the changes in the illumination settings are bound to have significant effect on the face appearance in such a way that the alterations between the images of the identical face on account of lighting can be greater than image changes caused by the modification in the face identity [6]. It is widely expected that the video-based face recognition techniques have immense potential in several applications where motion can be deployed as a signal for face segmentation and tracking, and the incidence of added data necessarily leads to enhancement in recognition efficiency.

Nevertheless, these techniques are troubled by their own hassles. The video sequence and the recognition techniques which are capable of integrating the data over the entire video [7]. The capacity of several techniques to tackle the face, pose and misalignment can be generally decided by the quantity of overt geometric data utilized by them the face representations [8]. The vital object of the face recognition mechanism is to segregate the traits of a face which are decided by the inherent shape and color of the facial surface from the given circumstances of image generation [9], [10]. The Illumination invariant in the non-sub-sampled contour let transform domain extracts the geometric structure devoid of pseudo Gibbs event around singularities and halo artifacts, which attributes to the qualities of non-subsampled contour let transform [11]. The Illumination Robust Dictionary-Based Face Recognition is based on concurrent sparse approximations against the backdrop of changing lighting. In this case, a dictionary is educated for each face class in accordance with the specified training examples which drastically reduces the representation fault with a sparseness restraint. Subsequently a test image is projected onto the span of the atoms in each skilled dictionary [12].

**LITERATURE SURVEY**

A lots of investigations make their way in the domain of literature, which area dedicated to the Face recognition. Given below is a concise account of some of the research works in this regard.

Mohan et al. [13] launched an innovative method of face recognition in accordance with the extraction of texture features to tackle the challenge thrown by the features which incredibly impact the face recognition technique such as the pose and illumination changes. With the intention of overwhelming the intricacy of employing the texture features on the whole image, it segregated the face into four segments and assessed the texture features in each and every segment independently. The texture features, in turn, were obtained from the co-occurrence constraints with diverse orientations, leading to the easy performance of the face recognition, without any modification in the pose, illumination and rotation. The test outcomes on the FG-NET aging database and Google Images evidently emphasize the consistency, viability and effectiveness of the innovative technique.

Chen et al. [14] proposed a novel technique for the face recognition or certification against the pose, illumination, and expression (PIE) changes by employing modular face features. A sub-image in low-frequency sub-band was extorted by a wavelet transform (WT) to curtail the image dimensionality. It was segmented into four parts for characterizing the local features and cutting back the PIE impacts, and the minute image in a rude scale was produced through the WT keeping intact the global face features. Altogether, five modular feature spaces were built up. The most distinguishing universal vectors in each feature space were located, and a nearest feature space-based (NFS-based) distance was evaluated for classification. The weighted summation was executed to integrate the five distances. The astounding test outcomes illustrated without doubt that the innovative technique was incredibly superior to the peer methods with regard to the recognition and validation rates.

J. Shermina and V. Vasudevan [15] gave a green light to an innovative face recognition technique which exhibited robustness in relation to the pose and lighting changes. For the purpose of processing the pose invariant image, the Locally Linear Regression (LLR) technique was employed to generate the virtual frontal view face image from the non-frontal view face image. In order to process the illumination invariant image, minimal frequency components of Discrete Cosine Transform (DCT) were utilized to customize the illuminated image. Taking into account, the fact of identifying the facial images which were both pose variant and illumination variant, the Fisher Linear Discriminant Analysis (FLDA) method and Principal Component Analysis (PCA) techniques were utilized. In the final stage, the scores of FLDA and PCA were integrated by means of a hybrid approach in accordance with the Feed Forward Neural Network (FFN). As per the scores accomplished in the preliminary recognition system, a weight was distributed to the image, which was distinguished by means of the corresponding weight allocated and the integration of scores. It was clear from the test outcomes on the
hybridization method that it was all around prepared to adequately distinguish the face images successfully.

Ajay et al. [16] assessed and contrasted the feats of several blends of the edge operators and linear subspace techniques to ascertain the combination for the pose classification. To assess the efficiency in execution of the innovative technique, they performed several tests on the CMU-PIE database consisting of images with extensive changes in lighting and pose. They were able to find that the feat of the pose classification invariably dependent on the selection of the edge operator and the linear subspace approach. The superb classification precision was achieved by the Prewitt edge operator and Eigen feature regularization method. With a view to successfully address the lighting oscillations, they deployed the adaptive histogram equalization as a pre-processing measure leading to the incredible improvement in the performance with the exception of that of the Robert’s operator.

S. Muruganantham [17] launched an innovative technique which furnished an up-to-date assessment of the vital human face recognition investigation. They were able to offer a summary of face recognition and its applications. Thus, a literary assessment of the largely employed face recognition methods was furnished. Explanations and constraints of face databases which were employed to assess the efficiency in execution of the related face recognition techniques were offered. The most significant factors impacting the face recognition mechanism was the pose illumination, identity, occlusion and expression. In the document, they spotlighted a critical analysis of the modern investigations linked to the face detection procedure. They offered an extensive assessment of vital investigations on the face recognition procedure dependent on several constraints. Moreover, a summarizing account of the Face recognition procedure together with the methods associated with the several constraints which have a telling impact on the face recognition procedure.

PROBLEM DEFINITION

The human activity identification has emerged as an unsolved issue, unsolved issue in spite of several monumental investigations have been carried in this direction. The human motion analysis in the computer vision detects human actions. It includes a wide-range of applications like the security watch, human machine interactions, video annotations, sports, therapeutic diagnostics and passage, way out control. Nevertheless, it proceeds as an exceptionally troublesome undertaking to distinguish human actions, in perspective of their variable looks and the broad extent of poses they can expect. In the case of classification, at times, linear classifiers are considered unsuitable for realistic issues as certain issues are endowed with the nonlinear property in the input space. However with the help of a nonlinear map, information may be mapped from the data space into a higher dimensional feature space. However, the issue is that the nonlinear mapping is unequipped for making any calculations. These issues are tackled by the SVM by bringing in the kernel functions. When the entire deficiencies are resolved in the literary works, the efficiency of our system can be considerably enhanced. However, the absence of any solutions for such deficiencies has motivated me to perform the investigational work in this regard.

Proposed methodology of Face Recognition System of Invariant Pose, Expression and Illumination using Modified Kernel based SVM

Let $D_b$ represent the database consisting of $N$ number of frames, and $F_i$ symbolize the database frames $F_i=(f_1, f_2, \ldots, f_N)$ size of $M \times N$. Thus, after furnishing an input (frame) from the database $D_b$, the user has to indicate the category of the image like the Expression, Left, Looking Down, Looking Up, Normal and Right Poses. In accordance with the captioned specification, the innovative works are exhibited below along with the comprehensive sections.

The innovative technique includes the following three phases.

- Pre-processing
- Feature extraction
- Classification

PRE-PROCESSING

The input image is initially treated with a set of pre-processing tasks in order that the image is adapted so as to suitable for the additional processing. In the innovative technique, the pre-processing process is initiated in which the color image is changed in to gray image to cutback the evaluation complication. In the case of the color image each image has diverse contrast and intensity values and hence we have changed the image in to gray image. In the gray
image all the image have the indistinguishable of 0 and 1, and the assessment complexity gets to be diminished in the gray image.

**Denoising using Gaussian Filter**

Let us suppose that the database $D_b$ tainted with noise, which paves the way for the reduction in the classification accuracy of the frames in the shape of various invariant poses like the Expression, Left, Looking Down, Looking Up and Right poses. Taking into account these tasks, the Gaussian filter is elegantly employed for the purpose of carrying out the function of denoising. As regards the pre-processing task, a Gaussian filter acts an effective filter in which the Gaussian function is devoted for the elimination of the noise. The technique obtains the input image, which is subjected to the pre-processing function, where the noise is eradicated by means of the Gaussian filter, leading to the accomplishment of the zero-noise output.

$$G(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}}$$  \hspace{1cm} (1)

The pre-processed frames from the database are expressed by means of Equation 2 and 3 appearing below.

$$D_b = F_i$$  \hspace{1cm} (2)

$$F_i = f_1, f_2, \ldots, f_N$$  \hspace{1cm} (3)

$D_b$ - denotes the database of the innovative technique $F_i$ - symbolizes the set of Frames in the database $f_1, f_2, \ldots, f_N$ - characterizes the converted frames

**Feature Extraction using GLCM**

One of the limitations of real time face recognition systems is the computational complexity. In the image analysis, one requires feature extraction method to reduce the processing time and complexity. The feature extraction is done in order to get the most important features in the image. Features are properties which describe the whole image and serves as an important piece of information that is subjected to solve the computational task related to specific application. For each face image, a feature vector is formed by converting the generated gray-level co-occurrence matrix (GLCM) to a vector and then it is used for classification. Gray-level co-occurrence matrix (GLCM) is the statistical method that examines the textures which takes into account the spatial relationship of the pixels.

Compare to GLCM, Principal Component Analysis (PCA) is a standard technique used in statistical pattern recognition and signal processing for dimensionality reduction and feature extraction. GLCM method is very competitive with state of the art face recognition other techniques such as Linear discriminant Analysis, Gabor Wavelets and Local Binary Pattern (LBP). Using smaller number of gray levels (bins) shrinks the size of GLCM which reduces the computational cost of the algorithm and at the same time preserves the high recognition rates. This can be due to the process of quantization which helps in suppressing the noise of the images at higher gray levels. Moreover, GLCM is a robust method for face recognition with competitive performance.

The Gray Level Co-Occurrence Matrix (GLCM) represents the numerical strategy of investigating the textures which take into account the spatial relationship of the pixels. The GLCM qualities symbolize the composition of an image by assessing the recurrence of event of the sets of pixel with determined qualities and in a specific spatial relationship in an image, creating a GLCM, and in this manner extorting the statistical measures from the related matrix. The graycomatrix capacity in MATLAB creates a gray-level co-event network (GLCM) by assessing the recurrence of a pixel with the intensity (gray level) $i$ in a specific spatial relationship to a pixel with the value $j$.

By default, the spatial relationship is briefly described as the pixel of significance and the pixel to its prompt right, however it is additionally conceivable to demonstrate other spatial connections between the two pixels as sought.

**FIGURE 1. Process of GLCM Matrix**

**Gray Level Co-Occurrence Matrix (GLCM)**

A GLCM constitutes a matrix as appeared in Figure 1 [18] in which the size of the matrix is indistinguishable to the
number of gray levels, $G_M$, in the image. The matrix component $T_{xy}(x, y|\Delta p, \Delta q)$ describes the comparing isolated by a pixel separation $\Delta p$, $\Delta q$. The matrix component is likewise meant as $T_{xy}(x, y|d, \theta)$ which is home to the second order probability values for the variety between the gray level $x$ and $y$ separation $d$ a particular edge $\theta$. Presently, a few attributes are obtained from the GLCM. $G_M$ symbolizes the quantity of gray levels utilized and mean of the same. $T_x(x)$ relates to the $x^{th}$ row of entry attained by aggregating the row of $T_{xy}(x, y)$.

$$T_x(x) = \sum_y T_{xy}(x, y) \quad \text{and} \quad T_y(y) = \sum_x T_{xy}(x, y)$$ (4)

$$\psi_p = \sum_x xT_x(x) \quad \text{and} \quad \psi_q = \sum_y yT_y(y)$$ (5)

$$\zeta_p = \sum_x (T_x(x) - \psi_p(x))^2$$ (6)

$$\zeta_q = \sum_y (T_y(y) - \psi_q(y))^2$$ (7)

With the efficient employment of the ensuing equations, we are able to estimate the diverse traits which can be effectively employed to train the classifier. In the current research, additional noteworthy traits are shortlisted for execution by appropriately deploying them.

**Area:**
The plain shape descriptor employed in the innovative technique represents the area. The area of a specific image is computed by means of Equation 8 shown as follows.

$$\text{Area}, E = \frac{I_g}{I_d}$$ (8)

Where,
$I_g$ represents the image height.
$I_d$ denotes the image width

**Perimeter:**
$$T_1 = 2(I_g + I_d)$$ (9)

**Circularity:**
The shape descriptor known as the circularity represents the measure of perimeter to that of the area in an image which is computed by means of the following Equation 10.

$$\text{Circularity}, U = \frac{E^2}{T}$$ (10)

**Auto Correlation:**
The relationship assesses the non-linear independency of gray levels of neighbouring pixels. The Digital Image Correlation speaks to an optical method which uses the changes in the images. This is habitually employed to evaluate deformation, displacement, strain and optical flow, as a very usual application for estimating the motion of an optical mouse. It is furnished by the following Equation 12.

$$A_r = \frac{\sum_x \sum_y (x, y)p(x, y) - \psi_x \psi_y}{\zeta_n \zeta_m}$$ (12)

**Contrasts:**
The contrast characterizes the variance of the gray level and is the difference between the maximum and the minimum values of a set of pixels. The GLCM contrast is invariably very much associated with spatial frequencies. It is calculated by the Equation 13 shown below.

$$S = \sum_x \sum_y (x - y)^2 T_{xy}(x, y)$$ (13)

Where, $E$ characterizes the area
$T$ symbolises the perimeter, which is calculated by the following Equation 11.

$$T = 2 \prod \sqrt{(I_d/2)^2 + (I_g/2)^2}/2$$ (11)
Cluster Prominence:

\[ CP = \sum_{x,y} ((x - \psi_x) + (y - \psi_y))^4 T_{xy}(x, y) \]  

(14)

Cluster Shade:

\[ CS = \sum_{x,y} ((x - \psi_x) + (y - \psi_y))^3 T_{xy}(x, y) \]  

(15)

Dissimilarity:

\[ Dis = \sum_{x,y} |x - y| T_{xy}(x, y) \]  

(16)

Homogeneity:

\[ Hom = \sum_{x,y} P(x, y) \left[ 1 + (x - y) \right] \]  

(17)

**FIGURE 3.** Extracted Features used for classification of output

**Energy:**

The Angular Second Moment is otherwise called the Uniformity or Energy. It reflects to the aggregate of squares of sections in the GLCM. It evaluates the image homogeneity and is found to be high when the image possesses excellent homogeneity or when the pixels are very identical.

\[ Energy = \sum_{x,y} T_{xy}(x, y)^2 \]  

(18)

**Entropy:**

This constraint effectively evaluates the disorder of an image. When the image is not textually identical several GLCM elements possess insignificant values, which indicate that the entropy is exceedingly large.

\[ Entropy = \sum_{x,y} T_{xy}(x, y) \log(T_{xy}(x, y)) \]  

(19)

**SUPPORT VECTOR MACHINES**

The SVM symbolizes a machine learning technique designed in accordance with the statistical learning theory and is fruitfully employed for classification and regression with high-dimensional space. The SVM classification technique is targeted at locating an optimal hyper plane. The optimal hyper plane represents segregation between two classes devoid of discreet faults, and incredibly enhances the segregating margin. A SVM algorithm was designed to locate the optimal hyperplane separating two classes with insufficient data. Nevertheless, an absolute test vector is highly essential for classification. To estimate the values of the missing elements from those in the entire set, a linear least square technique is employed. The vital objective of the SVM technique is to locate the hyperplane which considerably enhances the margin, and needs the solution of the following optimization issue. Considering non-linearly non-separable data, the target of most extreme edge characterization is to isolate the two classes by a hyperplane such that the separation to the support vectors is improved to the greatest. This hyperplane is known as the optimal separating hyperplane (OSH). The OSH equation is outfitted as takes after.

\[ f(x) = \sum_{i=1}^{l} \xi_i z_i V_i V + b \]  

(20)

Where \( \xi \) and \( b \) represent the solution of a quadratic programming issue.

SVM tries to locate an isolating hyperplane in the feature space, a Hilbert space for a binarization issue. The soft-margin SVM algorithm depends on the accompanying compelled minimization optimal issue:

\[ \min \frac{1}{2} r^T r + M \sum_{k=1}^{m} \xi_k \]  

(21)

Subjected to

\[ (s_k, r^T \varphi(Y_k) + a) \geq 1 - \xi_k \]  

(22)

\[ \xi_k \geq 0, k = 1, \ldots, m \]  

(23)

Where \( r \) is a vector normal to the hyperplane, \( a \) is an bias term such that \( a/||r|| \) speaks to the separation between the hyperplane, \( M \), is the soft margin parameter and the origin, \( \varphi : P \rightarrow H \) is a nonlinear mapping capacity, \( \xi_k \)'s are loose variables to control the preparation lapses, \( [\xi_1, \ldots, \xi_m]^T \), and \( M_k \in P^* \) is a penalty parameter for tuning the generalization ability.
Also, the general form of kernel function is given us,
\[ K(U, V) = \varphi(U)^T \varphi(V) \] (24)

Normally utilized kernel functions are of linear kernel, Polynomial kernel, Quadratic kernel, Sigmoid and Radial Basis function. The expressions for kernel functions are represented as below.

For Linear Kernel:
\[ K_{lin}(U, V) = u^T v + c \] (25)

Where \( u, v \) represents the inner products in linear kernel and \( c \) is a constant.

For Quadratic Kernel:
\[ K_{quad}(U, V) = 1 - \frac{\|u - v\|^2}{\|u - v\|^2 + c} \] (26)

Where, \( u, v \) are the vectors of the polynomial kernel function in the input space.

For Polynomial Kernel:
\[ K_{poly}(U, V) = (\lambda u^T v + c)^d, \lambda > 0 \] (27)

For Sigmoid Kernel:
\[ K_{sig}(U, V) = \tanh(\lambda u^T v + c), \lambda > 0 \] (28)

The adequacy of SVM relies upon the choice of kernel, the kernel’s parameters, and delicate soft margin \( M_t \). The parallel SVM can be stretched out to multiclass. Multiclass SVM’s are generally executed by consolidating a few two-class SVM’s either by one-versus-all techniques or one-versus-one strategy. On the off chance that if the feature space is straightly entwined, it must be mapped into a high dimensional space through Radial basis function kernel, so that the issue turns out to be directly divisible. The mix of any two kernel capacities can give preferable exactness over utilizing any of one kernel capacity.

Modified Support Vector Machines (Multi class Classification:)

In our Modified Support Vector Machines (MSVM) classification, the two kernel functions like linear and quadratic kernel functions are integrated to obtain better performance ratio. By integrating equations 25 and 26 the average is found out which is proposed in this technique. The integrated kernel function is used in the modified SVM and the average of the kernel function, \( K_{avg}(U, V) \) is given as follows,
\[ K_{avg}(U, V) = \frac{1}{2}(K_{lin}(U, V) + K_{quad}(U, V)) \] (29)

\[ K_{avg}(U, V) = \frac{1}{2}\left( (u^T v + c) + \left( 1 - \frac{\|u - v\|^2}{\|u - v\|^2 + c} \right) \right) \] (30)

In this technique, the color image is furnished as input and the color image are converted to gray image to avoid the computation complication. Thereafter, for the gray image the Gray Level Co-Occurrence Matrix (GLCM) technique is employed followed by the performance of the Support Vector Machine (SVM) classifier procedure [19], [20], [21]. However, in this modified Support Vector Machine we have to consider two kernels linear and quadratic to locate the hyperplane. By integrating these two outcomes, the average of the outcomes is obtained and employed to locate the hyperplane. Linear kernel function gives better performance in large data sets whereas quadratic kernel function for better accuracy and precision. Other than average of these two kernels, kernels with weight parameters \( \zeta \) and \( \xi \) can contribute better results, given as follows
\[ K_{wei}(U, V) = \xi (u^T v + c) + \zeta \left( 1 - \frac{\|u - v\|^2}{\|u - v\|^2 + c} \right) \] (31)

Where, \( \zeta = \delta \) and \( \xi = 1 - \delta, 0 < \delta < 1 \).

RESULTS AND DISCUSSION

This section puts in a nutshell the upshots realized together with the Modified Support Vector Machine(SVM). The experimental association along with recognition results is colorfully carved out below. The database has been extensively employed for acquiring the productivity from times immemorial. In this case, medical image database is used for the face recognition process.

The innovative method for the face recognition improvement is performed in a system having 8 GB RAM with 32 bit operating system having i5 Processor employing the MATLAB Version 2014a. In the novel technique, for arriving at the efficiency we have employed certain parameters which are shown below.
The sample input medical images gathered from the medical database is employed for the performance of the novel technique as illustrated in the following Figure 4. First, proposed techniques discussed thoroughly on this database and extended on standard data sets.

PERFORMANCE EVALUATION

The performance assessment of the innovative technique is carried out by estimating various parameters such as the accuracy, sensitivity and specificity of the method, and the related values are evaluated by means of the following expressions.

\[
\text{Sensitivity} = \frac{TP}{TP+FN} \tag{32}
\]

\[
\text{Specificity} = \frac{TN}{FP+TN} \tag{33}
\]

\[
\text{Accuracy} = \frac{TP+TN}{TP+FN+FP+TN} \tag{34}
\]

Where,

**True positive** (TP) represents the number of images which are accurately classified.

**True negative** (TN) characterizes the number of immaterial images which are accurately classified.

**False positive** (FP) signifies the number of pertinent images which are erroneously classified as immaterial images.

**False negative** (FN) relates to the number of immaterial images which are erroneously classified as pertinent image.

Selection of points for classification

The SVM classifier classifies the input image by means of taking the GLCM Features and the pixel intensity values. The pixel intensity values are obtained by selecting the significant points. The significant points include the areas of eyebrows (10 points), eyes (10 points), mouth (5 points), nose (5 points) and around face (10 points). The output classified image can be further obtained by comparing the pixel intensity values and the GLCM features.

Input/Output Images

Certain image samples chosen from the medical database images are employed for each category. Now, the images are categorized with regard to several invariant poses such as the Expression, Left, Looking Down, Looking up, Pose, Right poses shown in Fig. 5.

The consequent output images for the specified input are exhibited in the following Table 1 by means of the MATLAB. It is cheering to note that the outcomes achieved by the innovative technique are incredibly superior with respect to the invariant poses and illumination. Further, the diverse outputs for the specified input image are achieved and are contrasted with the input images, which also exhibited superlative outcomes for the epoch-making technique vis-a-vis those of the modern methods.

PERFORMANCE EVALUATION OF PROPOSED METHOD

The efficiency in execution of our enchanting technique is assessed with the assistance of several performance measures like the specificity, sensitivity and accuracy and which are elegantly exhibited in Figures 6. Further the charismatic technique is contrasted with the modern approach, which
The innovative technique along with several performance measures like the Accuracy, Sensitivity and Specificity for the entire kernel functions are exhibited in Table 2 and 3. The kernel functions relate to the quadratic, RBF (Rate basis function), polynomial and linear functions. The Accuracy, Specificity and Sensitivity metrics are found to be superior for the quadratic function which is 89.12%, 92.40% and 77.78% respectively. Moreover, the accuracy values for the RBF, Polynomial and linear functions are found to be 82.54%, 83.45% and 82.31% respectively. As regards the specificity measure, the corresponding values vary for the RBF, Polynomial and linear functions which are 86.55%, 88.01% and 86.26% respectively and the sensitivity values for the three functions are observed to be

<table>
<thead>
<tr>
<th>Performance</th>
<th>Existing Techniques</th>
</tr>
</thead>
<tbody>
<tr>
<td>Metrics</td>
<td>Quadratic</td>
</tr>
<tr>
<td>Accuracy</td>
<td>89.12</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>77.78</td>
</tr>
<tr>
<td>Specificity</td>
<td>90.40</td>
</tr>
</tbody>
</table>

The table above highlights the improved performance of the proposed kernel over existing techniques in terms of accuracy, sensitivity and specificity.
68.69%, 67.68% and 68.69% correspondingly. The innovative technique takes the average of both the quadratic and linear kernel functions to achieve superb outcomes.

FIGURE 6. Performance Measures of Proposed approach with Existing Techniques

Further, the comparison of all the modern kernel functions with regard to the performance metrics is furnished in Fig. 6 illustrating that our innovative technique attains superior efficiency which outsmarts those of modern methods and verified on YALE, JAFFE, PIE and FEI standard databases.

**Performance verification on standard databases**

The YALE face database contains 165 images of 15 persons (11 images per person). Images having different expressions like happy, sad, sleepy, surprised, wink etc in different lightning conditions. In this simulation, first 5 images of each person are taken as training images and remaining are used as testing images. Overall 75 face images are used as training images and 90 images as testing images and classified in pose, expression and illumination category as shown in Table 4. Table 5 shows comparison of performance of different methods Eigenfaces, ICA, 2DPCA, Kernel Eigenfaces and proposed model using PIE and YALE database. Tabular results show that proposed model achieved highest accuracy in comparison with other methods.

In the second simulation, first 6 images among 7 considered in previous simulation per person (Total: 6x10 = 60 images) in different expressions were used for training and the rest of 153 used for testing. Overall 7 times simulation is carried out. Similarly, Performance analysis after data partition of other database for performing various experiments shown in Table 6.

The JAFFE database contains 213 images of 7 facial expressions which includes 6 basic facial expressions and 1 neutral of 10 females. There are 3 or 4 images for each expression. First, a simulation is performed using the 7 images per person in different expressions and the remaining images for test. Thus, the total number of training and testing images became 70 and 143 respectively. figure 7

### Table 3. Performance Measures of Proposed Approach

<table>
<thead>
<tr>
<th>Performance Metrics</th>
<th>Proposed Approach</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>91.6</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>85.86</td>
</tr>
<tr>
<td>Specificity</td>
<td>92.69</td>
</tr>
</tbody>
</table>

### Table 4. Data partition on YALE database for performing various experiments

<table>
<thead>
<tr>
<th>SOE* Category</th>
<th>Training</th>
<th>Testing</th>
</tr>
</thead>
<tbody>
<tr>
<td>YALE_A1</td>
<td>Any one</td>
<td>All remaining</td>
</tr>
<tr>
<td>YALE_A2</td>
<td>Random 2 or 3</td>
<td>(i.e., remaining ten images except the one selected for the training)</td>
</tr>
<tr>
<td>YALE_A3</td>
<td>Random 6</td>
<td>Remaining 5</td>
</tr>
<tr>
<td>YALE_B1</td>
<td>a</td>
<td>b, c, d, e, j, k</td>
</tr>
<tr>
<td>YALE_C1</td>
<td>a</td>
<td>f, g, h, l</td>
</tr>
</tbody>
</table>

**Notes:**
- Training consists of experiments against illumination variation.
- Testing consists of experiments against expression variation.

### Table 5. Comparison of the Performance of different methods using YALE database (Note that ICA is tested using Euclidean distance in [22])

<table>
<thead>
<tr>
<th>Method</th>
<th>Total images</th>
<th>Recognized images</th>
<th>Recognition Accuracy(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eigenfaces [23]</td>
<td>165</td>
<td>118</td>
<td>71.52%</td>
</tr>
<tr>
<td>ICA [23]</td>
<td>165</td>
<td>118</td>
<td>71.52%</td>
</tr>
<tr>
<td>Kernel</td>
<td>165</td>
<td>120</td>
<td>72.73%</td>
</tr>
<tr>
<td>Eigenfaces [23]</td>
<td>165</td>
<td>139</td>
<td>84.24%</td>
</tr>
<tr>
<td>2DPCA [24]</td>
<td>165</td>
<td>147</td>
<td>89.09%</td>
</tr>
</tbody>
</table>

### Table 6. Performance analysis after data partition of other database for performing various experiments

<table>
<thead>
<tr>
<th>Data Sets</th>
<th>Training</th>
<th>Testing</th>
<th>Recognition</th>
</tr>
</thead>
<tbody>
<tr>
<td>PIE</td>
<td>636</td>
<td>617</td>
<td>97.04</td>
</tr>
<tr>
<td>YALE</td>
<td>165</td>
<td>162</td>
<td>98.6</td>
</tr>
<tr>
<td>JAFFE</td>
<td>153</td>
<td>147</td>
<td>96.07</td>
</tr>
<tr>
<td>FEI</td>
<td>173</td>
<td>145</td>
<td>83.81</td>
</tr>
</tbody>
</table>
Table 7. Recognition Accuracy of JAFFE database when training images per class varies from 7 to 1

<table>
<thead>
<tr>
<th>Training images/class</th>
<th>Total images</th>
<th>Recognized images</th>
<th>Recognition Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>7</td>
<td>143</td>
<td>141</td>
<td>98.60%</td>
</tr>
<tr>
<td>6</td>
<td>153</td>
<td>147</td>
<td>96.07%</td>
</tr>
<tr>
<td>5</td>
<td>163</td>
<td>156</td>
<td>95.70%</td>
</tr>
<tr>
<td>4</td>
<td>173</td>
<td>145</td>
<td>83.81%</td>
</tr>
<tr>
<td>3</td>
<td>183</td>
<td>148</td>
<td>80.87%</td>
</tr>
<tr>
<td>2</td>
<td>193</td>
<td>134</td>
<td>69.43%</td>
</tr>
<tr>
<td>1</td>
<td>203</td>
<td>136</td>
<td>66.99%</td>
</tr>
</tbody>
</table>

Table 8. Recognition Accuracy of methods across four datasets

<table>
<thead>
<tr>
<th>Data sets</th>
<th>LSVM</th>
<th>PCA</th>
<th>ICA</th>
<th>EF</th>
<th>PA</th>
</tr>
</thead>
<tbody>
<tr>
<td>PIE</td>
<td>83%</td>
<td>76%</td>
<td>80%</td>
<td>85%</td>
<td>97%</td>
</tr>
<tr>
<td>YALE</td>
<td>81%</td>
<td>82%</td>
<td>84%</td>
<td>87%</td>
<td>98%</td>
</tr>
<tr>
<td>JAFFE</td>
<td>89%</td>
<td>84%</td>
<td>81%</td>
<td>91%</td>
<td>96%</td>
</tr>
<tr>
<td>FEI</td>
<td>84%</td>
<td>83%</td>
<td>88%</td>
<td>87%</td>
<td>83%</td>
</tr>
</tbody>
</table>

shows the Seven training images of one female from the JAFFE database. Each face image has different expression.

Table 7 show the recognition accuracy for training images per class varying from 7 to 1. It also shows the number of correctly recognized images from total number of test images. The tabular results show that the recognition accuracy is more than 80% when system is trained using 3 or more than 3 images per class. The Recognition accuracy reduced to 66% when only a single image is used to recognized person in different expressions. Table 8 show the results on various data sets, as recognition accuracy is computed.

In which PIE data set, with illumination, expression and pose of 60 persons have been covered, proposed approach gives 97% accuracy. Similar performance achieved for more than 10 to 15 persons in the other data sets listed in Table 8. is maximum in the case of proposed approach, performance analysis compare to other existing methods LSVM, PCA, ICA, and EF. In simulation results, Accuracy of the algorithm for standard data set is calculated as with different experiments for one image in training and rest four in test set.
figure 9 shows the different frames of simulation results in which the person is correctly recognized in variation of illumination. Illumination varies from very low to high.

CONCLUSION

In this work, with an eye on fine-tuning the performance of face recognition, face images are detected and are assessed under various pose, expression and illumination scenarios. With a view to assess the face recognition, at first we choose the image from the database, and the technique proceeds through three phases such as the pre-processing, phase feature extraction and classification processes by means of the SVM. In the feature extraction procedure, the GLCM features are extorted. Subsequently, the SVM sets out for the face recognition. The innovative methods are competent to furnish superior visibility for various pose and illumination scenarios. The newfangled Face recognition method is performed in the working platform of the MATLAB. The performance of the innovative approach is assessed and contrasted with the modern methods techniques which have illustrated, verified on various standard data sets (YALE, FEI, PIE and JAFFE) and the fact that our dream scheme is illustrated, verified on various standard data sets (YALE, PIE and JAFFE).

REFERENCES


