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# A Comprehensive Overview of Face Recognition Approaches (Frameworks and Techniques)

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**ABSTRACT:**
Human face detection is an outstanding biometric system and also widely used in machine vision and pattern recognition, due to its good performance in a range of applications such as surveillance systems, legal, security, authentication, and smart cars. Recognition of the human face has always been faced with a variety of challenges, which often result in a reduction of facial recognition systems efficiency Therefore, to address these problems, we need to use sets of knowledge, techniques, and methods of different resources. Numerous biometric verification frameworks like Iris, Deoxyribonucleic Acid (DNA), Vein, Finger Print endures the issues of data acquisition. Face Recognition (FR) plays very important role in biometric systems. The recognition rate on the face is primarily dependent on the selection of attributes. This study investigates the FR techniques. Most current techniques are widely described in five stages, face image acquisition, preprocessing, feature extraction, classification, and attribute recognition. According to the available literature work, real-time Face Recognition biometrics needs still better performance, resistance to being spoofing attack, and needs better recognition accuracy. Recognition accuracy can be enhanced by advanced techniques such as neural networks using feature extraction algorithms. In this paper, the methods of facial recognition and work done by researchers have been collected and the challenges in this field have been investigated to pave the way for researchers and future research.

**KEYWORDS:** Face Recognition, Preprocessing, Feature Extraction, Pattern Recognition, Recognition Rate, Accuracy.

## 1. INTRODUCTION

Since there is a rapid growth in internet technology, every location in the community is more and more connected to a digital network. Everyday communication between each user and between several organizations is rapidly increasing through digital means. Since there is a large communication network, each person or user is identified by the unique personal identification number (PIN) in order to create a reliable connection. Although personal identification numbers such as identification cards work for each individual to authenticate the identity, since it is possible to hack work details, it is impossible to meet the security requirements. Biometric, the term got from Greek word Bio implies life and metrikos means measure, meaning estimation of life [1]. Authentication is based on behavioral or physiological attributes that can be considered to verify biometric identity until requirements meet the following requirements, Circulation, differentiation, universality, performance, acceptance, durability, and collectability. But, practically, no single biometric system satisfies all the requirements because of noisy data, spoof attacks, etc. This problem can be overcome by fusing more than one biometric system. In view of the quantity of Biometric attributes, the Biometric system is classified as Unimodal Biometric System and Multi Modal Biometric System. The biometric system is one of the successful applications of image processing. The person " s diagnosis using the face of a task is challenging because it involves the identification of three - a dimensional object from two - dimensional object. Basically, there are two approaches to identify a person through the face; the first approach involves extracting different types of features (space, shape, location, etc.) between facial feature and the second approach considers the whole image as a weighted combination of the standard face. For example, in the case of the diagnosis framework, the individual should acquire an iris design using a unique tool called (ophthalmoscope) And if the unique finger affects the individual, the person must hold his finger in the right direction. However, facial recognition overcomes these problems as it is non - interference or less expensive. The facial recognition system is very important because of its potential in solving other complex applications such as object recognition. Generally, Face Recognition or any biometric system including Finger Print, Palm Veins, DNA, Palm, Hand, Iris, Retina, and Voice is classified into two modes; Training Phase and Testing Phase. In the training phase, pre-processing and feature extraction is performed for all images in the database and a feature space is created where, as in the test phase, the attribute space is obtained during training and is used to identify with the unknown search page. The recognition of the challenging area face is the identification of the optical pattern recognition. The face is a three - dimensional object and is exposed to changes in state and state. Therefore, it must be detected based on the two - dimensional image. In general, a facial recognition mechanism can be implemented using four modules; acquisition of image (face - to - face), pre-processing, feature extraction, attribute matching. Facial recognition includes the segmentation of the desired area. If there is a video sequence, the identified figures should be monitored using the face detection element. Preprocessing is done on the identified face. preprocessing step involves measuring image, noise elimination, image retrieval. For better Recognition Rate. Further, Feature Extraction is carried out which provides valuable data using which it is very easy to discriminate faces of dissimilar people irrespective of geometrical differences.

The matching is performed by comparing the training set of attributes contained in the database with the test specification. Figure 1 shows the FR Process Flow involves the following steps; Image Acquisition, Preprocessing, Feature Extraction, Feature Matching and Database of Enrolled Users.

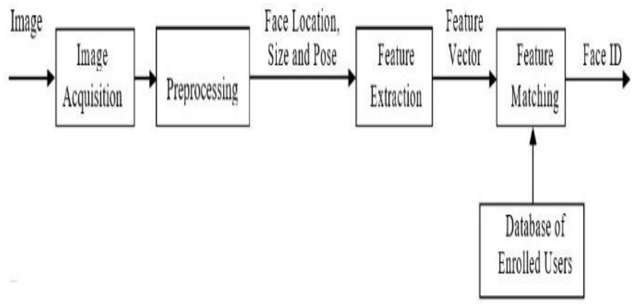


**Fig.1.**FR Process Flow

**A. IMAGE ACQUISITION**

Two main methods are available for recognition of the image (face). The first is the offline (non - real-time) method and the second is the online method (real-time). Typically, the Offline Method requires static images obtained from the standard face database like FERET, YALE, NIR, etc. In [2] the Face Recognition system is proposed by using the NIR database which includes different Pose, Illumination, Scale, and Blurring combinations. A Face Recognition system that uses color images from FERET Database is proposed in [3]. On the other hand, the Online Method acquires face images in a real-time environment from the image sensor typically a web camera. A Face Recognition system proposed in real-time which uses a web camera as image acquisition is presented in [4]. However, the use of web cameras suffers several problems like Illumination, Color Change, Lighting Variations, Spoof Attack, etc., While acquiring in a real-time environment. To overcome these problems, a real-time Face Recognition system to avoid Spoof Attack is presented in [5] by using polarized light during acquisition. Further, a thermal camera for image acquisition is proposed in [6] to avoid illumination change. A portable high-resolution mobile web camera is used for face image acquisition in [7] to avoid the blurring effect. A Near-Infrared Rays (NIR) based camera is utilized in [8] to capture the face image in the absence of ambient light for the implementation of an efficient face recognition system.

### B. PRE-PROCESSING

The preprocessing method is one of the most important steps in a biometric detection system, because it improves the detection accuracy by increasing the input image. In article [9], the normalization of lighting on face images is done using the Histogram equalization technique & it should be noted that this technique minimizes image contrast. In the paper [9], the normalization of brightness and sharpness has been done by analyzing the image into four non-overlapping regions and calculating the probability density function for each region at the same time. It should be noted that different types of noise such as impulse noise, Salt and Pepper Noise and Gaussian noise, etc. Can affect the image quality. Next, a middle filter is applied to the face image to remove Salt and Pepper Noise in [10]. Edge Detection is a very important method used in preprocessing to increase the edge area. A linear Gabor filter is used to increase the borders in the input image (view) [10]. The face recognition operation plays a very important role in the face recognition system, because face recognition makes it possible to extract the desired area of interest (face) and eliminates unwanted background. The facial area can be identified by a variety of techniques; in [11] a Viola Jones method is used to efficiently identify the face. A combination of the Locally Assembled Binary (LAB) feature and the Ada-Boost technique are used in [12] for face recognition. The skin color-based face recognition system used in the article [13], which includes converting the input RGB image to different color space such as YCbCr and HSV.

### C. CHARACTERISTIC TRACTION

Feature extraction is a process of extracting numerical features from a preprocessed image or a signal to remove weightlessness. The characteristics of the extracted test pattern are compared with the characteristics of the training data for verification. Various feature stretching techniques for the face biometric system have been proposed over the past decades. Principal component analysis (PCA) based on Eigenface facial feature extraction has been implemented in the paper [14]. In [23], local features of the face image are obtained using the Extended Local Binary Pattern (ELBP) technique. The PCA method is used to proportionally minimize the extracted properties. It should be noted that the feature sensors obtained after the feature extraction stage are compared with the faces of users registered in the database, and the feature matching match is performed and the Face ID corresponding to the face is generated.

### D. CLASSIFICATION

Classification is a very important and vital step in a biometric system. There are several different methods for classifying Test and Train properties, such as the neural network-based method, the fuzzy law-based method, the statistics-based method, the weight-based method, the multi-classifier-based method, and the classifier-based classifier method for Facial biometrics are used, among these methods. The classifiers that are based on machine learning are: Euclidean distance (ED), Hemingway distance (HD), Mahalanobis distance and Manhattan distance (MD) and so on. Facial features are classified using both ED and MD, and we compare the identification results of both classifications and then use the city block distance and Mahalanobis distance in the individual facial recognition system [61]. Finally, several multi-class classifiers are used to classify facial features, such as the nearest Neighbor Classifier (KNN) [62], the Support Vector Machine (SVM) [63], and Fuzzy Logic [64] And so on.

## 2. TEXT REVIEW

The Face Recognition is prominent research area because of the extensive applications in the fields of Industries, Manufacturing, Commercial, Construction, Healthcare, to protect law enforcement, Forensic Investigations and Social Media Platforms etc. This section gives the overview of various approaches and techniques along with their Recognition Rate, Accuracy and Database used etc. Local Ternary pattern (LTP) is used in [34] to extract the feature vectors from the Face image. Feature Extraction is transforming domain can also provide better performance. A Discrete Wavelet Transform based PCA Feature Extraction is proposed in [35]. PCA features are extracted by first converting the image from spatial domain to frequency domain using DWT. The Combination of Fast Walsh Hadamard Transform (FWHT) which was used to resolve illumination problem, Chiral Image Superimposition (CIS) which was used to resolve pose variation and Discrete Wavelet Transform (DWT) which was used for transformation has been proposed in [46]. A Binary Particle Swarm Optimization (BPSO) method is used to obtain the features from the transformed face image. Real-time feature extraction Discrete Cosine Transform (DCT) was performed in [47]. The dominant frequency components present in the image (face) are obtained using DCT and local features are obtained using zone DCT. Automatic Face Recognition system is proposed in [48] using Singular Value Decomposition (SVD). The obtained SVD features are classified using Hidden Markov Model (HMM). A combination of Local Binary Pattern (LBP) and Gabor Features are extracted in [49] for better recognition. Recognition Accuracy can be increased by extracting multiple feature extraction techniques. A Face Recognition system using Eigenface is proposed in [50], which involves extraction of facial features using PCA and the features are classified using Naïve Bayes Classifier. Fusion of LBP and Zernike features to extract Local and Global features are proposed in [60], authors reveal that fusion of these features provides reliable Face Recognition system. Recognition Rate of the face biometric can be increased by merging or fusing the features. In future fusion, the acquired biometric trait coming from different channels are preprocessed first, then the feature extraction technique is performed for each channel using different algorithms and finally combine the obtained features to form composite feature vector. In this paper we tried to cover different Face Recognition comparison approaches such as Databases and Techniques use, Accuracy and Recognition Rate obtained on the basis of Eigenfaces, Gabor Wavelet, Hidden Markov Model (HMM), Neural Network (NN) and Support Vector Machine (SVM). [72] S. Misra et al. have described the performance of Extreme Learning Machine (ELM) as a classifier for face recognition problem. Viola Jones algorithm was used for detecting and extracting the faces from the dataset. Histogram of Oriented Gradients (HOG) technique was used to extract the feature wherein authors have combined the Viola-Jones Algorithm for object identification, HOG for feature selection and Extreme Learning Machine (ELM) for patter classification for better recognition rate particularly for YALE dataset. The proposed scheme was tested on standard face recognition datasets from AT&T and YALE. The AT&T database contains 400 grayscale images of 40 persons. Each person has 10 images. The UMIST face database is a multi-view DB, consisting of 575 gray-scale images of 20 people. ORL database has images of 40 people, 10 images of each person. FERET database, which is a standard test-bed for face recognition technologies. 600 frontal face images corresponding to 200 subjects are extracted from the database for the experiments - each subject has three images of size 256×384 with 256 gray levels. The BANCA database consists of images from 52 subjects captured in 12 sessions. The FRAV2D facial database, containing 1000 frontal face images corresponding to 100 subjects, which are acquired under variable illumination and facial expression. XM2VTS database, comprises 2360 facial images that correspond to 295 distinct subjects. YaleB face DB, contains images of only 10 subjects. The database comprises a total of 5760 grey-scale facial images which were taken under 576 different viewing conditions (9 poses × 64 illumination conditions). CASIA database captured images of 123 subjects, with each individual having about 37 or 38 3D point clouds. The total number of range images is 4 625, including the variations in expressions, poses, occlusions and illumination, for each one also combined with other variations. The FRGC database is more recent. Based on the time of acquisition, the database can be divided into Spring 2003, Fall 2003 and Spring 2004, with over 4 900 subjects captured in 12 sessions. The FRAV2D facial database, containing 1000 frontal face images corresponding to 100 subjects, which are acquired under variable illumination and facial expression. XM2VTS database, comprises 2360 facial images that correspond to 295 distinct subjects. YaleB face DB, contains images of only 10 subjects. The database comprises a total of 5760 grey-scale facial images which were taken under 576 different viewing conditions (9 poses × 64 illumination conditions). CASIA database captured images of 123 subjects, with each individual having about 37 or 38 3D point clouds. The total number of range images is 4 625, including the variations in expressions, poses, occlusions and illumination, for each one also combined with other variations. The FRGC database is more recent. Based on the time of acquisition, the database can be divided into Spring 2003, Fall 2003 and Spring 2004, with over 4 900 range images from 557 people. 2,432 images of 38 individuals are considered from the Extended Yale Face Database B YALE DB contains grayscale images of 15 subjects in GIF format. In this experiment, we chose 5 individual subjects and considered 64 images per each subject (total 320 images). The BioID Face DB consists of 1521 gray level images. Each one shows the frontal view of a face of one out of 23 different test persons. IIT Delhi dataset contains 681 images of 75 subjects with different kinds of disguise variations. Task DB contains 21 subjects. For each subject we collected 2 sequences, where one has 322 frames and is used for training; the other has around 400 frames and is used for testing. In Mobo DB, there are 24 subjects. Each subject has 4 sequences captured in different walking situations Each sequence has 300 frames. The Yale face database contains 165 images of fifteen subjects.

**Table.1.**Face Recognition Comparison Approaches on the Basis of Eigenfaces

| Database | Methods Year Techniques | Accuracy | Remarks |
|---|---|---|---|
| AT&T, UMIST Face DB | [17] 2008 PCA RBF NN | Randomly partitioning DB: Best avg RR (93.05%) is achieved when 60, 70, 90 and 100 PCs are used. The max and min RR among 10 experimental runs (for PCs = 10-100) are found to be 95.50% and 85%.<br>N-fold cross validation test: Best avg RR (97.00%) is achieved when 50 and 60 PCs are used in the system. Max and min RR among the ten-folds experimental runs (for PCs = 20-60) are found to be 100% and 85%, respectively. Best avg RR of 94.10% is achieved using 140 hidden layer neurons and 60 PCs. Max and min RR over 10 experimental runs are 95.90% and 92.05%. | AT&T DB is used under the condition of minor variations of rotation and scaling, UMIST DB is used when the angle of rotation of the facial images is quite large. |
| RICE Face DB | [19]2010 Multiple Eigenface Subspaces | Best avg RR of 94.8% is achieved. 960 bitmap images of 120 individuals (60 male, 60 female), extracted from the RICE database is used. The training set, containing 60 images of different people of various gender, race and age taken under natural lighting conditions with neutral expression; test set containing 900 images (15 images of 60 people of various gender, race and age). | In terms of computational time, this method takes less training time than the generalized algorithm in all tested instances. Eigenface algorithm promise much for the field of facial image recognition but not before sometechnical refinement. |
| Olivetti, ORL Face DB | [21]2010 PCA FFBPNN | 97.018% | The eigenface method is very sensitive to head orientations, and most of the mismatches occur for the images with large head orientations. |
| Face94 | [18] 2012 PCA | 100% i.e., 0% FAR.<br>Increasing the number of images for each person in the training set to get best RR causes long computational time which increased exponentially with the database size. | The enhanced algorithm gives the same performance results in less time of recognition as 35% of the recognition time of the original algorithm. |
| ORL Face DB | [22]2010 Eigenface | Highest recognition rate of 97% is achieved when 15% of eigenfaces are taken with threshold value equal to 0.8 times of the maximum value of minimum Euclidian distances. | As the number of eigen faces are increasing, recognition rate goes on increasing. |
| | [20] 2006 EF, BPNN | The recognition performance is decreased dramatically if only one image per class used in learning phase. | When face images with different pose are added in learning step, RRincrease. |
| | [14] 2012<br>PCA EF | No. of Principal Components / Euclidean Distance / Manhatn Distane<br>5 / 77.5 % / 80%<br>20 / 97.5 % / 97.5%<br>190 / 97.5 % / 97.5% | 190 images of 38 different persons (5 images per person) of ORL DB is used. It can be concluded that, for recognition, it is sufficient to take about 10% eigenfaces with the highest eigenvalues. |
| FRAV Face DB | [16]2013 Eigenface | 96%<br>Total 510 face images of 51 different individual are selected to test the experimental results. | This method can only give good results for those images which have small amount of facial pose variation. |
| | [15] 2014 PCA Eigenfaces | 70%. From the test conducted, 21 face images were successfully recognized, while 3 faces were not detected, and 6 faces could be detected but not recognized by the system. In the original and testing images, it can be seen that the students have different postures and facial expressions therefore the system failed to successfully match bothimages. | The training database contains 46 images of 35 individual students. For testing, 35 images of 30 known and 5 unknown students were used. |

**Table.2.(A).**Face Recognition Comparison Approaches on the Basis of Gabor Wavelet

| Database | Methods Year Techniques | | Accuracy | | | Remarks |
|---|---|---|---|---|---|---|
| FERET Face DB | [27] 2005 GF, Improved AdaBoost Learning | | When only 140 features are used, the selected features achieve as high as 95.5% accuracy, which is about 2.5% higher than that of features selected by AdaBoost. | | | Training time of the proposed algorithm is only about 0.1 times longer than that of AdaBoost. |
| | [28] 2007 | | Variation Methods | Expression | Lightening | Huge number of features of Gabor face representation often brings about the problem of curse of |
| | | GT-LDA | GT-LDA | 98.24% | 89.18% | |
| | | GT-KDA | GT-KDA | 98.66% | 89.69% | dimensionality. In this a subset of the training set containing 540 images from 270 subjects for training was used. Two probe sets named fb (expression) and fc (lighting), which contains images with expression and lighting variation respectively, are used for testing against the gallery set containing 1196 images. The computational cost of the proposed algorithm is not increased very much. In the testing phase, the computational cost of the proposed method is nearly the same as the traditional LDA |
| FERET, BANCA FaceDB | [30] 2007 GW + GDA | | This method has achieved 97.5% recognition rate on the FERET database, and 5.96% verification error rate on the BANCA database. | | | FERET was used to test our algorithm for identification. Gabor + GDA method performs the best of the approaches considered, with only a 5.96% EER. The EER for the Gabor + KPCA method is around 10.36%, which is worse than the Gabor +PCA. |
| FRAV2D, ORL Face DB | [32] 2009 Gabor Responses, Bayesian PCA | | Database | Recognition Rate | | |
| | | | FRAV 2D | 99% | | |
| | | | ORL | 100 % | | |
| XM2VTS, Yale Face DB | [33] 2009 Principal Gabor Filters | | Experiments suggest that only three filter scales are needed to achieve the best performance with the proposed principal Gabor filters. Using more than three filter scales actually led to a decreased recognition performance. We can conclude that using principal Gabor filters instead of the classical Gabor filters results in a similar recognition performance; however, with a significant improvement in the computationalcomplexity,asonly24(3scalesand8orientations)insteadof40 filters are needed for computing the Gabor face representation. | | | In the experiments only a subset of the database featuring 640 facial images with frontal pose are used. |

**Table.2.(B).** Face Recognition Comparison Approaches on the Basis of Gabor Wavelet

<table>
<tr><th>Database</th><th colspan="2">Methods<br>Year<br>Techniques</th><th colspan="3">Accuracy</th><th>Remarks</th></tr>
<tr><td rowspan="2">Extended Yale B, AR, FERET faceDB</td><td rowspan="2" colspan="2">[29] 2010<br>GSRC,<br>Gabor Occlusion Dictionary</td><td>Occlusion Method</td><td>Sunglasses</td><td>Scarves</td><td rowspan="2">The number of atoms is significantly reduced in the computed Gabor occlusion dictionary, which greatly reduces the computational cost in coding the occluded face images while improving greatly SRC accuracy. A subset from the AR database consists of 1399 images from 100 subjects (14 samples each class), 50 male and 50 females. 799 images (about 8 samples per subject) of non-occluded frontal views with various facial expressions were used for training, while the others for testing. The computational cost is roughly reduced from about $O(\eta^2)$ with $\eta$=5779 to about $O(\kappa^2)$ with $\kappa$=899, where Gabor feature extraction consumes very little time<br>(about 0.19 second).</td></tr>
<tr><td>GSRC</td><td>93%<br>(5% higher than that of SRC)</td><td>79%<br>(20% higher than that of SRC)</td></tr>
<tr><td>FRGC 3D, CASIA 3D Face DB</td><td colspan="2">[26] 2012<br>3D GPSR</td><td colspan="3">98.37%<br>Computational analysis shows that 3D GPSR has only linear-time complexity on the dimensional reduction procedure, which is a huge improvement, compared to the ordinary approaches. SR has only linear-time complexity compared to the cubic-time complexity in other methods.</td><td></td></tr>
<tr><td>ORL, FRGCv2 FaceDB</td><td colspan="2">[31] 2013<br>M & P of Gabor, PCA, SVM</td><td colspan="3">99.9%. Use of the magnitude and the phase to represent face has an important influence on the performance of the application and the improvement of error rates.</td><td></td></tr>
<tr><td rowspan="5">Yale Face DB</td><td colspan="2">[24] 2010<br>2D-GF, SC</td><td colspan="3">90%</td><td>Lower recognition rates have got for mages representing rotated or non-frontal faces.</td></tr>
<tr><td rowspan="4">[25]<br>2014</td><td>PCA</td><td colspan="3">Average RR = 98.3%, Average Computation Time (ms) = 10</td><td rowspan="4">Recognizing a face image with Gabor filters is a computationally heavy task.</td></tr>
<tr><td>LGBPHS</td><td colspan="3">Average RR = 97.3%, Average Computation Time (ms) = 127,435</td></tr>
<tr><td rowspan="2">DPL</td><td>DPL6</td><td colspan="2">Average Recognition Rate = 99.2% Average Computation Time (ms) = 381</td></tr>
<tr><td>DPL25</td><td colspan="2">Average Recognition Rate = 99.7% Average Computation Time (ms) = 1,537</td></tr>
</table>

**Table.3.**Face Recognition Comparison Approaches on the Basis of Neural Network

<table>
<tr><th>Database</th><th>Methods Year Techniques</th><th colspan="3">Recognition Rate %</th><th>Remarks</th></tr>
<tr><td>Japanese Face DB</td><td>[37] 2003 RAN-LTM, ILA</td><td colspan="3">99%</td><td>The face detection method introduced here is still rather immature in terms of the computation costs and accuracy. we evaluate the recognition performance using another set of 3311 images, which consists of 1748<br>nonface images and 1536 non-registered faces.</td></tr>
<tr><td rowspan="3"></td><td rowspan="3">[36] 2007 HE, HF, NC, PCA, LDA, ANN, ED,</td><td>FE</td><td>Classifier</td><td>RR</td><td rowspan="3">The database consists of face images from twenty (20) individuals, each with ten (10) face images.</td></tr>
<tr><td>PCA</td><td>ED, NC, NN</td><td>91.85%, 91.85%, 92.59%</td></tr>
<tr><td>LDA</td><td>ED, NC, NN</td><td>90.00%, 92.22%, 85.56%</td></tr>
<tr><td rowspan="2">Yale Face DB</td><td>[38] 2007 ILDA, APCA</td><td colspan="3">At the end of experiment, we get the normalized errors equal to 0.121, 0.232 and 0.305 for the first, second and third LDA significantfeatures.</td><td>Low resolution images generate huge dimensional feature space.</td></tr>
<tr><td>[45] 2011 PCA, FFNN</td><td colspan="3">This method has the acceptance ratio is more than 90 % and execution time of only few seconds.</td><td>200 images from Yale database are taken.</td></tr>
<tr><td></td><td>[40] 2008 2D-DCT, SOM</td><td colspan="3">81.36%. Good face recognition performance is possible, even with<br>feature vectors that are dramatically reduced in size relative to the usual case for DCT based analysis.</td><td>DB of 25 face images, containing 5 subjects and each subject having 5<br>images with different facial expressions. Best RR achieved with the least amount of processing time is for the case of 850 training epochs.</td></tr>
<tr><td>BioID Face Database</td><td>[39] 2009 PNN, TMM</td><td colspan="3">Low spread values increase the number of falsely accepted and rejected images and high values fail to confirm correct classification.</td><td></td></tr>
<tr><td>AT &T DB</td><td>[41] 2011</td><td colspan="3">92.40%</td><td></td></tr>
<tr><td></td><td>SOM</td><td colspan="3"></td><td></td></tr>
<tr><td>ORL Face DB</td><td>[44] 2011 RBFN, LDA, CT</td><td colspan="3">This method produces better RR of 98.6%, acceptance ratio of 85 % and execution time is only a few seconds</td><td>The number of images increased to LDA based curvelet with RBFN takes 67 sec forexecution</td></tr>
<tr><td>IIT-Delhi Face DB</td><td>[42]2012 NN-SOM</td><td colspan="3">88.25% to 98.3%. The learning took approximately 9 seconds and<br>the recognition took less than a second</td><td></td></tr>
<tr><td rowspan="3"></td><td rowspan="3">[43] 2013 BPC, RBF</td><td>Network</td><td>RR</td><td>Training Testing time</td><td rowspan="3">The face database consists of 90 images. Out of 90 images, 64 images are taken for training the networks</td></tr>
<tr><td>BPN</td><td>96.66%</td><td>3.6549 sec</td></tr>
<tr><td>BPN+ RBF</td><td>98.88%</td><td>3.6492 sec</td></tr>
</table>

**Table.4.** Face Recognition Comparison Approaches on the Basis of Hidden Markov Model

| Database | Methods Year Techniques | Recognition Rate % | Remarks |
|---|---|---|---|
| ORL Face DB | [54] 2003 HMM, WC | 100% | |
| | [53] 2008 7 State HMM, Quantized SVD | The experiments showed a recognition rate of 99%, using half of the images for training. The system has been evaluated on 64×64 jpeg resized YALE database too. This database contains 165 face images with 231×195 pgm format. Using five training image, 97.78% recognition rate was obtained where for six trainingimages the recognition rate was 100%. | Yale DB: Train time per image(second)=0.53 to 0.54, Recognition time per image(second): 0.15. ORL DB: Train time per image(second)=0.46 to 0.63, Recognition time per image(second): 0.15 to 0.28 |
| Task, Mobo Face DB | [58] 2003 Adaptive HMM | Recognition Rate<br>Database \| Temporal Markov Model \| HMM<br>Task \| 93% \| 96%<br>Mobo \| 98.4 % \| 98.8% | |
| ORL, FERET Face DB | [56] 2006 BaselineHMM, Maximum Confidence HMM | Baseline HMM (ORL DB) \| MCHMM (ORL DB)<br>95.5% Recognition Rate \| 97% Recognition Rate | Using ORL DB, randomly selected 5 images as training images and the other 5 images as test images. FERET DB containing sufficient facial variations was adopted for evaluation. 153 human classes selected with at most eight images provided for each class. Recognition time usingFERETDBfordimensions10,12,14,16,18and 36 is 0.25, 0.30, 0.38, 0.43, 0.55, 1.67 (in sec) respectively. |
| BANCA FaceDB | [51] 2007 GWF, DCT CF, HMM, GOD | Window Size \| Average Accuracy \| Maximum Accuracy<br>13 \| 95.23 % \| 96.15%<br>15 \| 96.85 % \| 98.08%<br>17 \| 93.15 % \| 95.00% | BANCA DB contains 52 subjects (26 female and 26 male). For each subject, 12 different sessions.<br>. |
| GTFD, FERET Face DB | [55] 2008 MC HMM | Non-HMM methods using Eigenface and Fisher face are implemented. The class numbers *C*=50 and *C*=100 are used. For the case of *C*=50, ML-HMM obtain recognition accuracy 89%, which is improved to 92.4% using MCE-HMM and 94.4% using MC-HMM with*d*=16. | When MC-HMM with *d*=36 is implemented, and achieved the accuracy as high as 95.6%. Eigenface and Fisher face attain accuracies of 80% and 81.3%, |
| AT&T, Essex Faces95 , FERET Face DB | [57] 2008 DWT, Haar, Gabor, Coiflet WL, S-HMM | Recognition Rate = 97%<br>Training time per image = 4.31 sec<br>Classification time per image = 3.45 sec | Essex Faces95 DB contains 20 color images each of 72 individuals. For the FERET database, 4 images per individual were used for training, with the remaining image being used for testing. |
| ORL Face DB | [52] 2011 2D-DWT, HMM | When tested with a subset of the AT&T (ORL) database, up to 90% correct classification and as low as 0.02 FAR were achieved. | 30 features per sub image were sufficient to give the best performance. The average time for testing a face was approximately 0.15s, which is near real-time. |
| ORL, Yale Face DB | [59] 2013 Sub-Holistic HMM | ORL Database \| Yale Database<br>Resolution \| Recognition Rate \| Resolution \| Recognition Rate<br>112X92 \| 99.5% \| 163X240 \| 99.39%<br>37X23 \| 98.75% \| 100X100 \| 98.78%<br>18X15 \| 95.25% \| 30X30 \| 94.54% | Face image divided into 3 quadrants, top left, top right and lip portion. This division is beneficial to reduce the recognition time. Recognition Time Per image (sec) for Resolution of 1,2,3,4,5 for ORL database is 0.124, 0.11, 0.093, 0.089, 0.07 and for Yale database is 0.172,0.144, 0.11, 0.109, 0.091. |

**Table.5.** Face Recognition Comparison Approaches on the Basis of Support Vector Machine

| **Database** | **Methods Year Techniques** | **Recognition Rate %** | | | | **Remarks** |
|---|---|---|---|---|---|---|
| | | | SVM Using Kernel Functions | | | |
| Yale, AR Face DB | [65] 2003 ICA, SVM | Database | p=1 | p=3 | Gaussian | Yale Face DB contains 165 images (11 per individual).<br>AR Face Database 300 face images (12 per individual) was used. |
| | | Yale | 99.39 % | 99.39 % | 99.39 % | |
| | | AR | 93.33 % | 92.67 % | 94% | |
| FERET, AT&T Face DB | [67] 2011 2D-PCA, SVM | 2DPCA – SVM on AT&T Database: Accuracy=97.3% 2DPCA – SVM on FERET Database: Accuracy=95.1%<br>k-NN classifier can achieve the accuracy rate 100% with k=1. However, in practice, it is the worst classifier because it has high structural risk. | | | | The FERET DB contains 1564 sets of images for 14,126 images that include 1199 individuals and 365 duplicate sets of images. AT&T DB contains 400 images of 40 individuals; each person has ten images. |
| XM2VTS Face DB | [68] 2006 ALDA, SVM | ECOC - Mink-Sigmoid = 96.69% BHC - Mink-Sigmoid = 93.23% | | | | DB contains 4 recordings of 295 subjects taken over a period of four months. Each recording contains a speaking head shot and a rotating head shot. |
| ORLFace DB | [69]2008 Kernel PCA, LS-SVM | The experimental results on the front 20 persons' faces in ORL face database show that KPCA based on LS-SVM has a up to 95% correct recognition rate, and a faster computational speed. | | | | PCA has the defects as requiring a large storage space and a large computational complexity, and perhaps losing important discriminative information after dimension reduction |
| | [70] 2009 | The results show that the correct recognition rate is up to 96%, and the | | | | |
| | CT, LS-SVM | computational speed is faster. | | | | |
| | [66] 2011 ICA, SVM | 96% | | | | |
| | [71] 2008 CBSVM | 96.1% | | | | The performance of the proposed method is, training time and testing time are both less than 6s. |

**3. CONCLUSION**

This paper examines different classification techniques and investigates the features that have been introduced in the facial recognition system since the last decade. Most current techniques are widely described in five stages, face image acquisition, preprocessing, feature extraction, classification, and attribute recognition. The biometric recognition rate depends mainly on the selection of attributes. This method provides a general framework, forecasting techniques, feature extraction algorithms, and classification for face biometrics. Eigen features are obtained from the image (ace) using the PCA technique which yields an accuracy of 97%. However, the use of the Eigen features technique has some limitations since Recognition Accuracy reduces for real-time images. In addition, this paper shows the extraction of features in amplitude conversion using Gabor Wavelets and Discrete Wavelet Transforms (DWT) and the extracted features are classified using neural network classifiers. Although, these methods provide better Recognition Rate for images from different databases but the performance degrades if a face image contains occlusions, sunglasses, beard, blurred image etc. The hidden Markov model (HMM) uses the support vector machine to provide better results for high - resolution images using the support vector machine. Various techniques have been introduced to improve recognition rates for facial recognition systems ، But the technical implementation that achieves better diagnosis accuracy for offline images and real-time images is still challenging. To overcome these problems, our research work takes advantage of combining local structural information with multi-directional characteristics. The combination of these techniques is expected to provide better identification rates compared to existing techniques.

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