



Face and Iris Based Multimodal Biometric Systems: Issues-Challenges and Open-Research Problems

¹ Sanjeevakumar M. Hatture, ² Vaishnavi V. Kulkarni

Department of Computer Science and Engineering, Basaveshwar Engineering College (Autonomous),
Bagalkot - 587103, Karnataka State, India

¹E-mail: smhatture@gmail.com , ² E-mail: vkulkarni817@gmail.com

Abstract : Digital India initiatives envisage the e-commerce and digital money transactions to the network society which make the human life more comfortable. At the same time, intruders/hackers are also attracted to perform unauthenticated and vulnerable activities with people's digital wallets/accounts. Hence it is necessitated to develop an effective security/authentication system to detect and prevent such attacks on the people digital wallets/accounts worldwide. The effective security/authentication system can be built with multi-biometric systems. An effective multimodal biometric system can build with face and iris traits to increase human recognition accuracy and increased security level. Face recognition is the technique for spotting or verifying someone's identification based totally on their appearance. Iris Recognition is a biometric manner of acknowledging human beings by analyzing distinct patterns present in the eyes. In this paper the extensive literature review on face, iris and their fusion is carried-out to identify issues and challenges imposed. The novel methodology is proposed to build multimodal biometric system with hybrid level of fusion and fusion rules employing Adaptive Neuro-Fuzzy Inference System (ANFIS). The scope for the research community is also explored.

IndexTerms - Multi-modal biometrics, Face recognition, Iris Recognition, Fusion Levels, ANFIS.

I. INTRODUCTION

With the rising cases of cybercrime, hacking of personal accounts, criminal and terrorist attacks, due to this there is a necessity for a personal identification system based on biometrics. A Biometric system is used for authentication and confirmation. Biometrics is an automated technique that distinguishes an individual based on physical (face, hand, iris, fingerprint) and behavioral (keystroke, signature, voice, gait) attributes, which are peculiar as well as cannot be forgotten or forged. The unimodal biometric system makes use of only one source of information for authentication besides suffers from various hindrances such as noisy information, non-universality, intra-class variation, inter-class variation, and spoof attacks. To overcome these difficulties multimodal biometric systems are utilized. A multimodal biometric system considers two or more parameters for evaluation that provides a high recognition rate. Face and iris recognition techniques are adopted and used enormously in various security fields such as public transport, airport security, military, banking, commercial applications, tech firms, universities, central and state governments. Face recognition is a manner of authenticating the face of a person through a machine. Face recognition is friendly and can be captured remotely which does not violate the privacy of the user. By considering the face as a single trait the system can't distinguish among identical twins. The face recognition system is affected by several environmental factors and also it is not effective at identifying people of color. The face recognition system gives accurate results moreover it is highly effective when combined with the iris biometric trait. Iris recognition is a type of biometric identification technology that uses distinctive patterns to identify people. Iris formation is a chaotic process and the iris patterns will be unique even for identical twins. Not only for the twins but also individuals possess unusual left and right iris patterns that are steady all over life. Face recognition algorithms such as Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and Local Binary Patterns Histograms are commonly used to distinguish faces (LBPH). Following that, Gabor wavelets and feature descriptor approaches are used. Face recognition is also performed using neural networks, deep learning approaches and transfer learning techniques using pre-trained models such as VGG16, VGG19, Facenet, ResNet50, InceptionV3, and Xception. Daugman's methods are most often used for iris segmentation and normalization. Gabor filters, Wavelet transform, Laplacian of Gaussian filter, Hilbert transform, Discrete cosine transform (DCT), as well as Discrete wavelet transform (DWT) are the approaches used to extract features. Weighted Euclidean Distance (WED), Jaccard Coefficient, and Dice Coefficient, Hamming distance, Euclidean distance, and Mahalanobis distance methodologies can be deployed for matching. The image can be fused by applying different levels of fusion such as sensor level fusion, feature level fusion, score/rank level fusion, and decision level fusion. Fusion can be classed in two levels particularly before and after matching. Fusion strategies that take place previous to matching are sensor and feature level fusion next to

matching are score/rank and decision level fusion. In sensor level fusion the crude data from the sensors are directly fused and the features extracted from distinct biometric modalities are merged in feature level fusion. In Score/rank level fusion the matching scores are gathered from numerous matchers and the decisions made by the distinct matchers are consolidated in decision level fusion. Using several rules such as AND rule, OR rule, Majority voting, Min- Max rule, Sum rule, Product rule, Weighted sum rule, Weighted product rule, Logistic regression, Borda count method, Dempster Shafer theory of evidence, Behavior Knowledge space, Figure of Merit and Symbolic object image is fused.

2. RELATED WORK

In this section exhaustive literature review is carried out to identify the research gap, scope and different issues and challenges of multimodal biometric system using face and iris modalities.

2.1 Face Biometric Systems

The person can be automatically authenticated using face biometric modality which can be collected remotely. Several researchers have proposed the methods of efficient person identification using facial biometric.

M.Geetha et al., 2021 [1] presented an eigenface method for face to keep track of candidates during online exams. Support Vector Machine (SVM) model with hinge loss function was applied to improve the accuracy. With 50 real-time photos in the dataset, the embeddings were retrieved with 61 percent accuracy by a Caffe-based DL face detector.

Sharmila et al., 2019 [2] explained a method that uses haar cascade and applied Eigenface, Fisher face, and Linear Binary Pattern Histograms (LBPH) methods that achieved the accuracy of 80%, 78%, and 80% respectively.

Maheen Zulfikar et al., 2019 [3] presented an approach that utilizes a convolutional neural network (CNN) on a dataset that consists of 9000 facial images of 30 subjects. Tested on five pre-trained models such as Alexnet, VGG16, SqueezeNet, ResNet18, and ResNet50.

Sanjeevakumar M. Hatture and Shanmukhappa A. Angadi 2019 [4] unveiled a novel method for face recognition that uses symbolic representations with graphs which contains texture information. Further described face image as a grouping of three fully connected graphs and extracted the features using symmetric local binary pattern (CS-LBP) descriptor. AR and VTU-BEC-DB databases were used for performing experiments that gained an accuracy of 97.33% and 97.25% respectively.

Vishwanath C. Kagawade and Shanmukhappa A. Angadi 2018 [5] proposed a new approach using is a multi-directional local gradient descriptor (MLGD) derived from local directional gradient features that make use of edge/line information in various directions. The datasets used are AR and LFW databases that gained recognition rates of 97.33% and 97.25% individually.

Neel Ramakant Borkar and Sonia Kuwelkar 2017 [6] explained a hybrid face recognition method that integrates two techniques PCA and LDA. The performance of the algorithm was evaluated on the AT&T dataset that obtained 97% accuracy when implemented on the raspberry pi 3 board.

Shanmukhappa A. Angadi and Vishwanath C. Kagawade 2017 [7] introduced a robust face recognition approach through symbolic modeling of polar Fast Fourier Transform features (FFT) were modeled as symbolic data. Evaluated on AR, ORL and LFW face databases that achieved an accuracy of 96.25%, 100%, and 97% respectively.

Xavier Fontaine et al., 2017 [8] created a Robust Sparse Coding (RSC) technique for automatic face alignment that solves the weighted-LASSO issue with an input image that is a convolution of the training examples. The datasets used were AR and LFW, which had accuracy of 95.0 percent and 96 percent, respectively.

Rajeev Ranjan et al., 2016 [9] suggested a method called hyperface, that utilizes (R-CNN) Region-based Convolutional Neural networks for recognition. Further, it fuses the in-between layers of a deep CNN network by means of a discrete CNN along with multi-task learning set of rules which operates on the fusion of features.

Soumendu Chakraborty et al., 2016 [10] presented a local gradient hexa pattern (LGHP) method for determining the correlation between the reference and its neighborhood pixels at various distances and derivative directions and applied on Extended YALE B, CMU-PIE, color-FERET, LFW, and Ghallager dataset.

Florian Schroff et al., 2015 [11] presented a system called FaceNet that uses a deep convolutional network and triplet loss function. The methods were evaluated on Labeled Faces in the Wild (LFW) and YouTube Faces datasets and attained 99.63% and 95.12% individually.

Rajeev Ranjan et al., 2015 [12] designed a new face detector Deep Pyramid Single Shot Face Detector (DPSSD) that is fast and detects faces with a vast-scale variation. Inception ResNet-v2 and ResNet-101 models were trained using various datasets such as IARPA Janus Benchmarks A, B, and C (IJB-A, IJB-B, IJB-C), and the Janus Challenge Set 5 (CS5).

Adrian Rhesa Septian Siswanto et al., 2014 [13] explained a method that uses PCA, Eigenface, Fisherface, and haar cascade for classification that gained an accuracy of 90%.

Alpika Gupta et al., 2014 [14] a simple approach that uses the viola jones algorithm which merges the geometric and symmetric facts from the image's face sections and was implemented on the Bao dataset.

Michel Owayjan et al., 2013 [15] designed a system and applied various methods such as Morphological operations, Filtering, Resizing on a proprietary dataset that achieved 90% accuracy.

Most of the techniques for person recognition using face modality adopt textural features as compared to geometrical, structural and appearance based methods. In-order to enhance the performance of the recognition system the raw facial images are preprocessed using enhancement techniques like Adaptive Histogram Equalization (AHE), Histogram Equalization (HE), resizing, (CLAHE) contrast limited adaptive histogram, (DOG) Difference of Gaussian, frequency domain filters, etc. The user authentication is performed by using the soft computing classifiers like SVM, cascade classifier, KNN, Fuzzy logic, CNN, etc. The degree of recognition accuracy varies between 60% and 100% due challenges imposed by the face recognition system like illumination, pose variation, occlusion, ageing etc. The summary of the face recognition techniques are depicted in Table 1.

Table 1: Unimodal Biometric System Using Face

Ref.	Methodologies/ Feature Extraction	Dataset used/ Number of Images	Classifier and Accuracy
[1]	Caffe based DL face detector, Triplet Loss Function	Proprietary Dataset (50 images)	Support vector Machine(SVM) and 61%
[2]	Haar cascades, LBPH, Fisherface, Eigenface	Proprietary dataset	Haar-cascade Classifier, LBPH=80%, Fisherface=70% and Eigenface=70%
[3]	Viola-Jones algorithm, Adaboost, Haar Features	9000 facial images of 30 subjects	convolutional neural network SqueezeNet=98.76%, Resnet model =99.41%
[4]	symmetric- local binary pattern (CS-LBP), Viola-Jones algorithm	VTU-BEC-DB, AR Face Database	VTU-BEC-DB= 97.20% AR Face Database=97.97%
[5]	Multi-directional local gradient descriptor (MLGD)	LFW and AR	LFW=97.25% AR=97.33%
[6]	PCA and LDA	AT&T dataset	PCA=91%, LDA=94%, PCA+LDA=97%
[7],[50]	Viola-Jones algorithm , 2D-DFT, 1D-PFFT	AR, ORL and LFW	AR=96.25%, ORL=100%, LFW=97%
[8]	Mesh warping, Robust Sparse Coding (RSC) algorithm	AR, LFW	AR=95.0% and LFW=96%
[9],[46]	Viola-Jones algorithm, Iterative Region Proposals (IRP)	AFW, PASCAL and DDB	Robust Region-based CNN (R-CNN)
[10]	Local gradient hexa pattern (LGHP)	Extended Yale B, CMU-PIE, color-FERET, LFW	1 NN
[11]	FaceNet Deep Neural Network	LFW, YouTube Faces	KNN, LFW= 99.63% YouTube Faces= 95.12%
[12]	Deep Pyramid Single Shot Face Detector (DPSSD)	UFDD, FDDB, PASCAL	ResNet-101 and Inception ResNet-v2 mAP of 0.706, 0.969 and 96.11%.
[13]	PCA, Eigenface, Fisherface	Proprietary Dataset	Haar cascade, 90%
[14]	Viola-Jones algorithm	Bao Dataset	Haar Classifier
[15],[47]	Morphological Operations	Proprietary Dataset	90%

Further another trait extracted from the facial image is Iris. In the ensuing section the different existing methodologies available for the Iris modality is explored.

2.2 Iris Biometric Systems

The different techniques and approaches employed for personal authentication using iris biometric modality are summarized here. Anfal Waled Al-zanganawi and Sefer Kurnaz [16] proposed a method that uses a Genetic algorithm (GA), feature extraction by Daubechies wavelets. 90% accuracy was attained using the support vector machine (SVM) classifier.

S Bharadwaj et al., 2021 [17] developed a new framework for iris recognition that utilizes watershed change and a 4-level Haar wavelet for feature extraction. UBIRIS.v2 dataset is considered that gained a recognition rate of 96.96%.

Omar Medhat Moslhi 2020 [18] introduced a new iris segmentation method that employs a deep convolutional neural network (CNN) with the DenseNet-201 iris classification model. On the CASIA Iris-Thousand, CASIA Iris Interval, UBIRIS Version 1 , and UBIRIS Version 2 datasets, the system achieved an accuracy of 99.32 percent, 100 percent, and 98.29 percent respectively..

Hammou Djalal Rafik and Mechab Boubaker, 2020 [19] Used the knowledge gained from the weights that have been pre-trained in ImageNet's dataset and data-augmentation process is made easier using applied transfer learning. The MMU1 database was used to test the VGG16, DenseNet169, and Resnet50 CNN models, which yielded accuracy of 96.10 percent, 93.50 percent, and 98.70 percent, respectively.

Shweta M. Nirmanik and Sushmita Attarawala 2020 [20] suggested a Hough transform-based automatic segmentation method that can locate the ring-shaped iris and pupil region, obstructing eyelashes, eyelids and reflections. Feature extraction through 1D Log-Gabor filters and hamming distance for classification tested on UBIRIS and CASIA databases.

Swati D. Shirke and C. Rajabhushnam 2019 [21] proposed a method that uses Probabilistic Neural Network (PNN) algorithm. Spatial FCM was applied for segmentation on the CASIA V4 database.

Bhagyashree Deshpande and Deepak Jayaswal 2018 [22] described a system that utilizes the 1D log-Gabor filter method for feature extraction that achieved high accuracy of 95% on the UTIRIS V.1 dataset.

Chandrashekar M Patil and Sushmitha Gowda 2017 [23] proposed an effective approach which uses multiple feature extraction methods such as Gray Level Co-occurrence Matrix (GLCM), Hausdroff Dimensions (HD), Histogram of Oriented Gradients

(HOG) and Biometric graph matching (BGM) and 2D - Gabor Filter methods. The SVM gives the best accuracy of 95%, WED and Jaccard Coefficient and Dice Coefficient provide recognition of around 90% on CASIA V4 dataset.

Shanmukhappa A. Angadi and Vishwanath C. Kagawade 2017 [24] presented a new symbolic data modeling approach based on a savitzky-golay filter to extract energy features from enhanced images. SGGsIE&T and CASIA V4 datasets are considered for evaluation and gained 99.3% and 94.86% respectively.

Kamal Hajaria et al., 2016 [25] used an integrated approach of LBP and GLCM, designed two innovative algorithms for eliminating noise and a texture feature extraction method were developed. For this study, the CASIA and MMU iris databases were used.

Mazhar Sajjad et al., 2016 [26] suggested a unique contrast-limited adaptive histogram equalization approach for improving the quality of deteriorated iris images while dealing with non ideal iris images (CLAHE). The EER achieved was 18.82 percent using the NICE-II database.

Aalaa Albadarneh et al., 2015 [27] described a method based on texture and shape based attributes. The system was tested using UBIRIS.v1 IRIS dataset and the recognition rate using HOG, Gabor plus DCT, GLCM, Gabor plus DCT, and GLCM and integrated all features which provide recognition rate of around 20%, 76%, 96%, 92%, and 92% respectively.

Zi Wang et al., 2015 [28] presented a novel approach where mixed convolutional and residual networks (MiCoReNet) with Rectified Linear Units (ReLU) are trained for eye recognition. The system achieves 99.08 percent and 96.12 percent on the CASIA-Iris-IntervalV4 and UBIRIS.v2 datasets respectively.

Himanshu Rai and Anamika Yadav 2014 [29] selected the zigzag collarette area for extraction of unique features since that area captures the most essential portions of the iris. The method was evaluated on CASIA and Chek databases that achieved an accuracy of 99.91% and 99.88% respectively.

Yung-Hui Li and Marios Savvides 2013 [30] modeled the underlying probabilistic distributions using Figueiredo and Jain's Gaussian Mixture Models (FJ-GMMs). Experiments were performed on ICE2 and UBIRIS datasets and both have achieved an accuracy of 90%.

In order to extract the iris pattern from the eye images the localization of pupil plays vital role. The different approaches employed for iris segmentation are the Integro-differential operator, Log Gabor, HAAR transform, Canny Edge Detection, and Hough Transform. Further iris normalization is performed with Daugman's rubber sheet model. The degree of accuracy achieved by using these approaches is around 90%.

The summary of the Iris recognition techniques are depicted in Table 2.

Table 2: Unimodal Biometric System Using Iris

Ref.	Methodologies/ Feature Extraction	Dataset used/ Number of Images	Classifier and Accuracy
[16]	Genetic Algorithm, Daubechies wavelets	Proprietary Database	Support vector Machine (SVM) ,90%
[17]	4-level Haar Wavelet, watershed transform	UBIRIS.v2	Hamming distance , 96.96%
[18]	Morphological Process, and Contour Detection	CASIA Iris Interval, Casia Iris-Thousand, Ubiris v1 & Ubirisv2	DenseNet-201, CASIA Iris Interval= 99% ,Casia Iris-Thousand=100% Ubiris v1=99.32 & Ubirisv2=98.29%
[19]	Convolutional Neural Network (CNN)	MMU1	VGG16=96.10%, DenseNet169=93.50% and Resnet50=98.70%
[20]	1D Log-Gabor filters	UBIRIS and CASIA	Hamming distance
[21]	Spatial FCM, Hough transform, Daugman's methods	CASIA V4	Probabilistic Neural Network (PNN)
[22]	1D Log-Gabor filters	UTIRIS V.1	Hamming distance , 95%
[23]	Gray level covariance matrix(GLCM), Hausdroff Dimensions (HD), Biometric graph matching (BGM) and 2D Log-Gabor filters	CASIA V4	SVM =95%, WED=90% and Jaccard Coefficient and Dice Coefficient=90%
[24]	savitzky-golay filter energy, hough transform, canny edge, Daugman's methods	SGGSIE&T and CASIA V4	SGGSIE&T=99.3% CASIA V4=94.86%
[25]	LBP and GLCM	CASIA and MMU	Radial basis kernel and probabilistic neural network, 96.5%
[26]	CLAHE, 1D Log-Gabor filters	NICE-II	Hamming distance, EER= 18.82%
[27]	GLCM and DCT	UBIRIS.v1	Logistic model tree (LMT), Weighted Euclidean distance (WED) and 70% to 90%
[28]	Mixed convolutional and residual network (MiCoReNet)	CASIA-Iris-IntervalV4 and	CASIA-Iris-IntervalV4= 99.08% and UBIRIS.v2= 96.12%

		UBIRIS.v2	
[29]	Haar wavelet decomposition and 1D Log Gabor wavelet	CASIA and Chek	SVM and Hamming distance, 99.91% and 99.88%
[30]	Figueiredo and Jain's Gaussian Mixture Models (FJ-GMMs)	ICE2 and UBIRIS	90%

2.3 Face and Iris Based Multimodal Biometric System

In-order to alleviate the limitations imposed by face and iris unimodal biometric system and to enhance the recognition accuracy both viz. face and iris, biometric information is integrated at different level. Several integration methods and rules are presented by the research community and are summarized here.

Parneet Kaur and Komal Sood 2021 [31] described (AL-CNN) ant lion-convolutional neural network method using score and decision level fusion. Kernel Principal Component Analysis (KPCA) method applied for face and iris feature extraction. The datasets used are FERET and CASIA V3 gained an accuracy of 98%

S. Anu H Nair et al., 2020 [32] used (PCA) principal component analysis and implemented feature level fusion on ORL and CASIA databases. Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT) techniques methods for feature extraction, and Normalized Cross-Correlation (NCC) method for template matching.

Basma Ammour et al., 2020 [33] applied (NIG) normal inverse gaussian analytical attributes along with multi-resolution 2D Log Gabor with Dimensionality reduction using spectral regression kernel discriminant analysis (SRKDA) and Fuzzy k-nearest neighbor (FK-NN) for classification. 99.16% and 99.33% accuracy were attained on CASIA-ORL and CASIA-FERET databases, respectively.

Vishwanath C. Kagawade and Shanmukhappa A. Angadi 2020 [34] implemented feature level fusion using Polar Fast Fourier Transform (PFFT) and the Canonical Correlation Analysis (CCA). The datasets used are ORL, LFW, VISA, and CASIA.4.0 which gained 99% accuracy.

Muthana H. Hamd and Marwa Y. Mohammed 2019 [35] presented a robust multimodal system using feature-level fusion on ORL, CASIA-V1, and MMU-1 databases. Fourier Descriptors (FDs) methods achieved a 97.5% accuracy rate that uses Euclidean distance for template matching.

Md. Zahidur Rahman et al., 2019 [36] used the PCA and Daugman's methods for face and iris recognition. Feature extraction by 1-d Log Gabor filter. The YALE and CASIA V1.0, ORL and CASIA V1.0 databases have achieved 97.78% and 100% accuracy respectively.

Basma Ammour et al., 2018 [37] proposed an effective method that uses hybrid fusion. The features are extracted by a 2D-log Gabor filter and are taken from the face and two iris (left and right) modalities. The system was evaluated on the CASIA Iris Distance database. The recognition rate i.e. EER is up to 0.24%.

Basma Ammour et al., 2018 [38] implemented hybrid fusion by employing feature and score fusion levels by applying different rules such as max rule, min rule, sum rule, and weighted sum rule.

Yacine bouzouina and Latifa hamami 2017 [39] described a method that combines the Discrete Cosine Transform (DCT) with (PCA). The Gabor filter and Zernike moment use feature selection with a Genetic Algorithm and SVM classifier to achieve feature level fusion. The database employed the CASIA-IrisV3-interval, which had 98.8% accuracy.

Basma Ammour et al., 2017 [40] presented an effective approach used score level fusion is implemented with min and max rules. Feature extraction by 1D Gabor wavelets. Datasets used ORL and CASIA-V3-interval and gained an accuracy of 98%.

Manasa G et al., 2016 [41] suggested a method using histogram-based feature extraction and normalized the features using a z-score model. Implemented feature level fusion on Standard database from google.

Pawan K. Ajmera et al., 2015 [42] used min-max normalizing with the score level fusion. The datasets used were CASIAv1 and FRGCv2, which achieved more than 85% improvement.

Guang Huo et al., 2015 [43] presented an effective method based on feature level fusion and built a special two-dimensional Gabor filter bank. The datasets CASIA V1.0, CASIA V4-Lamp, ORL, and PIE-Illum achieved a recognition rate of 98.33%, 98.9%, 90.83%, and 99.63% respectively.

Valentine Azom et al., 2015 [44] introduced a novel hybridized fusion strategy that uses a decision level fusion rule with maximum, minimum, and average voting methods to merge three classifiers based on feature and score level fusion. The ORL face and CASIA iris datasets were used to validate the approach, which yielded a high identification accuracy of 98.75 %.

Maryam Eskandaria and Önsen Toygar 2012 [45] presented a robust system based on global and local feature extraction methods based on Local Binary Patterns. Face and iris scores were normalized using tanh normalization before fusion. ORL, FERET datasets for face and CASIA, and UBIRIS datasets for iris, and overall accuracy of 97% was achieved.

The biometric information is fused at different levels such as sensor level, feature level, score/rank level and decision levels. Among them the feature level and score/rank level fusion provides the highest recognition rate by applying different fusion rules such as Majority voting, Min-Max rule, Sum rule, Product rule, weighted sum rule, weighted product rule etc. and gained an accuracy between 85% and 99%.

The exhaustive literature review provides the bird eye vision of various works carried out for user authentication by employing face and iris modalities. It is observed that multi-modal biometrics systems achieve better security and higher level of accuracy. In future multi-biometric system will lead the security applications and provide dynamic updating of user information and avoid spoof attacks [48, 49].

The face and Iris based multimodal biometric system summary is provided in the Table 3.

Table 3: Multimodal Biometric Systems Using Face-Iris Trait

Ref.	Methodologies/ Feature Extraction	Fusion Level	Dataset used/No. of images	Classifier and Accuracy
[31]	Kernel Principal Component Analysis (KPCA)	Score and Feature Level Fusion, Sum, Max, Min, Weighted Sum Rules	FERET and CASIA V3	(AL-CNN) ant lion-convolutional neural network, 97.7%
[32]	DCT, DWT	Feature level and PCA based image fusion	ORL and CASIA	Normalized Cross Correlation (NCC)
[33]	(SSA) singular spectrum analysis and spectral regression kernel discriminant analysis (SRKDA)	Score and Decision Level Fusion, Sum, Max, Min, Weighted Sum, OR Rules	CASIA-ORL and CASIA-FERET	Fuzzy k-nearest neighbor (FK-NN) and CASIA-ORL=99.16% and CASIA-FERET=99.33%
[34]	Polar Fast Fourier Transform (PFFT) and the Canonical Correlation Analysis	Feature Level Fusion	ORL, LFW, VISA and CASIA.4.0	Nearest Neighbor algorithm (NN), 97%
[35]	Gray Level Co-occurrence Matrix (GLCM), LBP, PCA, Fourier Descriptors (FDs)	Feature Level Fusion Serial Rule	ORL, CASIA-V1 and MMU-1	Euclidean distance ORL and CASIA-V1 PCA=97.5%,FDs=97.5%,GLCM=10%,LBP=100%,ORL and MMU-1 PCA=97.5%,
[36]	PCA, labor masek method, 1-d Log Gabor filter	Score and Decision Level Fusion Weighted sum rule	YALE and CASIA V1.0, ORL and CASIA	Euclidean distance YALE and CASIA V1.0=97.78% and ORL and CASIA V1.0=100%
[37]	2-d Log Gabor filter, SRKDA, viola jones algorithm	Feature, Score and Decision Level Fusion, OR rule	CASIA Iris Distance Database	Euclidean distance EER is 0.24%
[38]	2-d Log Gabor filter, SRKDA, viola jones algorithm	Score and Decision level and sum,max, min, weighted sum rules	CASIA Iris Distance Database	Euclidean distance FAR = 0.06% at GAR = 99.5%
[39]	DCT,PCA, Gabor filter, Zernike moment, Genetic Algorithm	Feature Level Fusion	CASIA-IrisV3-interval	Support vector machine (SVM) 98.8%
[40]	1D Gabor wavelets, Hough, Snake and Distance regularized level set (DRLS) , DCT and PCA	Score Level Fusion ,min-max rule	ORL and CASIA-V3-interval	Hamming distance 98%
[41]	Discrete cosine Transform(DCT)	Feature Level Fusion , Z-score	Standard database from google	Euclidean distance
[42]	LBP, Daugman's algorithms	Score Level Fusion	CASIAv1 and FRGCv2	Chi square distance, Hamming distance 85%
[43]	2-D Gabor filter	Score Level Fusion, min-max rule	CASIA V1.0, CASIA V4-Lamp, ORL and PIE-illum	SVM CASIA V1.0=98.33%, CASIA V4Lamp=98.9% ORL= 90.83% PIE-illum=99.63%.
[44]	PCA and LDA , Full Width at Half Maximum (FWHM)	Score Level Fusion	ORL and CASIA	SVM 98.75%
[45]	LBP.LDA, Mean-Variance Normalization (MVN),	Score Level Weighted, Sum Based Rule, MinMax Normalization	ORL, FERET and CASIA and UBIRIS	Nearest Neighbor Classifier 97.0%

3. Issues and Challenges

Research community working on the domain of Biometric system with face and Iris traits tried to provide the solutions to the issues reported in the literature. Some of the issues and challenges identified in Face and Iris Recognition are enlisted below:

1. Occlusion: denotes obstruction and is one of the most crucial factors that influence the face recognition system. occluded face means the face is not visible completely. face is covered using sunglasses, caps, scarf, mask etc.
2. Pose variations: a face recognition system is highly susceptible to pose variation and is one of the difficult tasks to analyze and to determine the orientation of a face.

3. Effect of illumination: illumination stands for brightness variations. face and iris recognition systems are extremely sensitive to the light reflections.
4. Ageing: due to the ageing factor the sometimes the system cannot be able to recognize the person accurately.
5. Complex background: during face image acquisition the background information may embed with facial information and reduce the recognition accuracy.
6. Low resolution: if the facial image has a resolution lower than $16*16$ then it is known as low resolution image. this exists mainly in camera-based applications such as cctv and supermarket security cameras.
7. Skin color: face recognition systems are highly sensitive and have high error rates in identifying dark-skinned people.
8. Iris localization: due to the existence of undesired data such as sclera, lashes, pupil, and other areas of interest, as well as the region of interest it is difficult to locate the iris. iris segmentation is a challenging task in iris identification since it involves extraction of iris patterns.
9. Low quality images: when the image captured in an iris recognition system is of poor quality and contains random reflections in and around the iris, the performance of the system is greatly altered.

Further some of the open research issues need to be addressed are enlisted in the following

4. SCOPE FOR THE RESEARCH

1. Face and iris feature extraction is a challenging and irregular process due to complex backgrounds.
2. Face and iris image decomposition and merging can be utilized for copyrighting and verification.
3. Examine how deep learning can be used to obtain greater representations from information, which can then be integrated using regular machine learning to calculate relevant attributes.
4. Scope to enhancement of performance in Unimodal biometric system, by addressing the issues like corrupted data present in the sensors, intra-class variation, non-universality and different types of spoofing assaults.
5. To develop the real-time biometric system with a dynamic enrollment of the user in the system.
6. Feature extraction from the face and iris modalities using multi-scale representations to gather relevant and discriminative information.
7. Face and iris trait extraction from an image by employing enhancement technique.
8. To work in the direction of establishing a more robust iris extraction for biometrics in order to improve overall precision.
9. The iris region of interest (ROI) image can be located and segmented by the usage of deep learning auto-encoders.
10. To improve the system's ability to handle visual degradation due to noise and glasses. The color feature can also be used to improve recognition accuracy.
11. Developing optimal algorithms for noisy artifacts removal which is present on distinct datasets such as ICE, PHOENIX, and UBIRIS etc. for enhancing the accuracy.
12. Robustness of the face recognition may be tested with diverse variations in faces angles.
13. Reduction in the processing resource requirements and minimization of error rates are necessitated in modern biometric systems.
14. Advanced deep learning methodologies required for faster authentication in large populated biometric security systems.
15. Facial recognition systems are also affected by domain adaption and dataset bias. More complex object detection tasks such as human and multi-view object detection need to explore.
16. An intelligent human robot needs to be designed for higher level of security applications by employing facial and iris modalities.
17. Developing efficient algorithms for several purposes such as to detect human, pose variation and in the same time, object recognition, and pedestrian detection.
18. Designing of 3-D face recognition system using the combination of multiple cameras.

5. PROPOSED MODEL

Face and iris based multi-modal biometrics systems using adaptive hybrid level fusion with ANFIS based fusion rule is proposed and shown in figure 1. Both face and Iris modalities are extracted from acquired facial image.

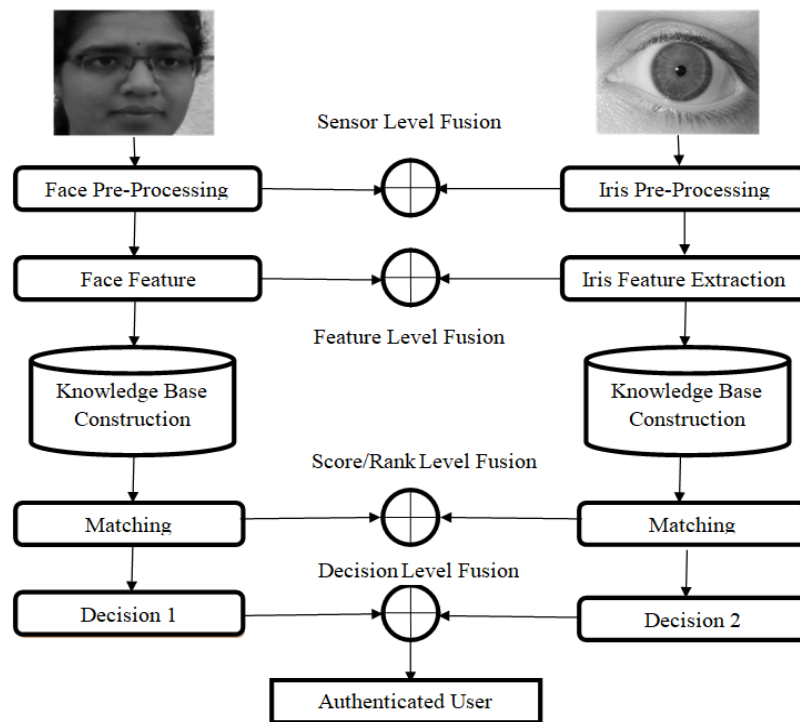


Figure1. Face and Iris Based Multimodal Biometric System with Hybrid Fusion Level

The image enhancement can be done in both the spatial and frequency domains. The different enhancement techniques employed in spatial domain are namely mean, median, gray level transformations, histogram processing and Gaussian smoothing etc. Similarly the different enhancement techniques used in frequency domain are namely 1-D and 2-D Fourier transforms, homographic filtering, ideal and Gaussian low pass filters. To extract geometrical and textural features from face there is a need to apply different face recognition algorithms. From iris the features such as stripes, freckles, coronas are extracted by 1-D and 2-D Gabor wavelets. The knowledge base is constructed by extracting hidden information from various face and iris images available in the data gallery. At several phases, such as sensor, feature, score/rank, and decision, the information derived from the face and iris attributes can be combined. Furthermore the machine learning techniques are employed for making a decision regards to authentication.

Biometric information fusion takes major role in Multimodal biometric systems. The fusion level and rules of fusion is chosen according to the information collected from the biometric traits. The spoof attacks are also targeted by the intruder if the fusion level/rule is known in advance. Hence to mitigate the risk of spoof attacks on multimodal biometric systems the hybrid fusion level and adaptive fusion rules are necessitated to protect from the intruder. In the proposed multimodal biometric system a wise technique will be developed where adaptiveness can be achieved using an adaptive neuro-fuzzy inference system (ANFIS) which can dynamically select fusion level and rule according to the uncertain behavior of the multimodal biometric system.

6. EXPERIMENTATION

The experimental results obtained by the various researchers worked in the domain of Face and Iris based Biometric systems are enlisted in the Table 4.

Table 4: Accuracies of Face, Iris and Face-Iris Modalities

Biometric System	Recognition Accuracy of the System with Challenges Addressed	
	Minimum	Maximum
Unimodal Biometric System using Face	60%	100%
Unimodal Biometric System using Iris	90%	100%
Face and Iris Based Multimodal Biometric System	85%	99%

The experimental results reported for the unimodal biometric system with facial trait has an accuracy ranging between 60% to 100% and 90% to 100% for iris trait. Multi-modal Biometric System Based on Face and Iris has recognition rate ranging from 85% to 99%.

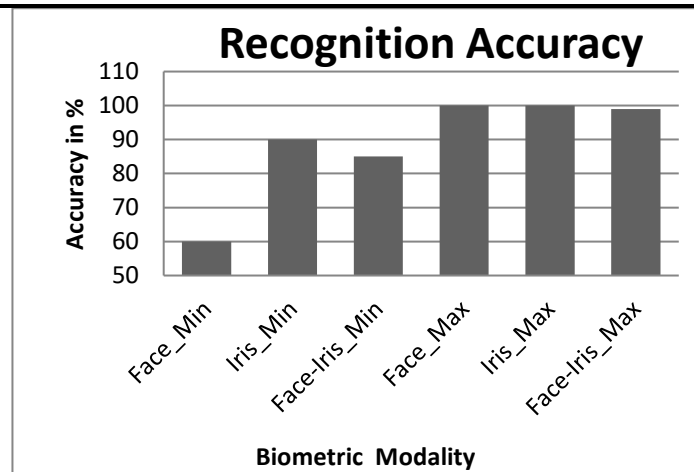


Figure2. Recognition Accuracy

Figure 2 provides an analysis of minimum and maximum recognition accuracy of Face, Iris and Face-Iris based multimodal biometric system.

7. CONCLUSION

Biometrics is unquestionably one of the field that is constantly evolving and have been thoroughly investigated, studied, and explored for the user authentication. One of the prominent online identity verification method is face biometric which is user-friendly. Iris trait is also collected from a facial image and contains distinct patterns which are stable throughout life. The higher recognition rate is achieved by combining facial and iris information. In this paper, an extensive literature survey is carried out separately for the unimodal biometric systems employing face and iris. Further literature review of different approaches proposed by the various researchers for multimodal biometric system using face-iris modalities is also explored and presented. The scope for the research community by enlisting various issues, challenges and open research problems is also explored. An efficient multimodal biometric system model is proposed where hybrid fusion levels is used according to the level of security and availability of the biometric formation. Further an adaptive fusion rule is proposed namely adaptive neuro-fuzzy inference system (ANFIS) and experimented to achieve higher level of security/ authentication for the end user.

REFERENCES

- [1] M.Geetha, S.K.Nivetha, R.S.Latha, S.Hariprasath, S.Gowtham, C.S.Deepak "Design of Face Detection and Recognition System To Monitor Students During Online Examinations using Machine Learning Algorithms" International Conference on Computer Communication and Informatics (ICCCI) Coimbatore, India, pp. 1-4, Jan. 27 – 29, 2021.
- [2] Sharmila, R. Sharma, D. Kumar, V. Puranik and K. Gautham, "Performance Analysis of Human Face Recognition Techniques," 4th International Conference on Internet of Things: Smart Innovation and Usages (IoT-SIU), pp. 1-4, 18-19, April 2019.
- [3] M. Zulfiqar, F. Syed, M. J. Khan and K. Khurshid, "Deep Face Recognition for Biometric Authentication", *International Conference on Electrical Communication and Computer Engineering (ICECCE)*, pp. 1-6, 2019.
- [4] Angadi, Shanmukhappa & Hatture, Sanjeevakumar "Face Recognition through Symbolic Modeling of Face Graphs and Texture" International Journal of Pattern Recognition and Artificial Intelligence, 2019.
- [5] Kagawade, Vishwanath & Angadi, Shanmukhappa, "Multi-directional local gradient descriptor: A new feature descriptor for face recognition" *Image and Vision Computing*, 83. 10.1016/j.imavis.2019.02.001, 2019.
- [6] N. R. Borkar and S. Kuwelkar, "Real-time implementation of face recognition system," *International Conference on Computing Methodologies and Communication (ICCMC)*, pp. 249-255, 2017.
- [7] Shanmukhappa A. Angadi and Vishwanath C. Kagawade "Face recognition through symbolic data modeling of local directional gradient" © Springer Nature Singapore Pte Ltd. 2018 N.R. Shetty et al. (eds.), *Emerging Research in Computing, Information*.
- [8] X. Fontaine, R. Achanta and S. Süsstrunk, "Face recognition in real-world images", *IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP)*, pp. 1482-1486, 2017.
- [9] Ranjan, Rajeev & Patel, Vishal & Chellappa, Rama, "HyperFace: A Deep Multi-Task Learning Framework for Face Detection, Landmark Localization, Pose Estimation, and Gender Recognition" *IEEE Transactions on Pattern Analysis and Machine Intelligence*, PP. 1-13, 2016.
- [10] S. Chakraborty, S. K. Singh and P. Chakraborty, "Local Gradient Hexa Pattern: A Descriptor for Face Recognition and Retrieval", in *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 28, no. 1, pp. 171-180, Jan. 2018.
- [11] F. Schroff, D. Kalenichenko and J. Philbin, "FaceNet: A unified embedding for face recognition and clustering," *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 815-823, 2015.
- [12] R. Ranjan *et al.*, "A Fast and Accurate System for Face Detection, Identification, and Verification," in *IEEE Transactions on Biometrics, Behavior, and Identity Science*, vol. 1, no. 2, pp. 82-96, April 2019.
- [13] A. R. S. Siswanto, A. S. Nugroho and M. Galinium, "Implementation of face recognition algorithm for biometrics based time attendance system," *International Conference on ICT for Smart Society (ICISS)*, pp. 149-154 2014.
- [14] Alpika Gupta, Dr. Rajdev Tiwari "Face detection using modified viola jones algorithm" *International Journal of Recent Research in Mathematics Computer Science and Information Technology* Vol. 1, Issue 2, pp: (59-66) 2014
- [15] Owayjan, Michel & Dergham, Amer & Haber, Gerges & Fakhri, Nidal & Hamoush, Ahmad & Abdo, Elie, "Face Recognition Security System", 2013.
- [16] A. W. Al-zanganawi and S. Kurnaz, "Human Biometrics Detection And Recognition System Using SVM And Genetic Algorithm Iris As An Example," *4th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)*, pp. 1-4, 2020.

- [17] S Bharadwaj “Improved biometric iris recognition using watershed transform” Journal of Physics: Conference Series Conference on Smart and Intelligent learning for Information Optimization (CONSILO) 2021.
- [18] Omar Medhat Moslhi, “New full Iris Recognition System and Iris Segmentation Technique Using Image Processing and Deep Convolutional Neural Network,” *International Journal of Scientific Research in Multidisciplinary Studies*, Vol.6, Issue.3, pp. 20-27, 2020.
- [19] H. D. Rafik and M. Boubaker, “A Multi Biometric System Based on the Right Iris And The Left Iris Using The Combination Of Convolutional Neural Networks”, *Fourth International Conference On Intelligent Computing in Data Sciences (ICDS)*, pp. 1-10, 2020.
- [20] Shweta M. Nirmanik, Sushmita Attarawala “Iris recognition system” Journal of Emerging Technologies and Innovative Research (JETIR), Volume 7, Issue 5 pp. 578-584, May 2020.
- [21] S. D. Shirke and C. Rajabhushnam, “Biometric Personal Iris Recognition from an Image at Long Distance”, *3rd International Conference on Trends in Electronics and Informatics (ICOEI)*, pp. 560-565, 2019.
- [22] B. Deshpande and D. Jayaswal, “Fast and Reliable Biometric Verification System Using Iris”, *Second International Conference on Inventive Communication and Computational Technologies (ICICCT)*, pp. 456-460, 2018.
- [23] C. M. Patil and S. Gowda, “An Approach for Secure Identification and Authentication for Biometrics using Iris”, *International Conference on Current Trends in Computer, Electrical, Electronics and Communication (CTCEEC)*, pp. 421-424, 2017.
- [24] S. A. Angadi and V. C. Kagawade, “Iris recognition: A symbolic data modeling approach using Savitzky-Golay filter energy features”, *International Conference on Smart Technologies for Smart Nation (SmartTechCon)*, pp. 334-339, 2017.
- [25] Hajari, Kamal & Gawande, Ujwalla & Golhar, Yogesh, “Neural Network Approach to Iris Recognition in Noisy Environment”, *Procedia Computer Science* 2016.
- [26] M. Sajjad, C. Ahn and J. Jung, “Iris Image Enhancement for the Recognition of Non-ideal Iris Images”, *KSII Transactions on Internet and Information Systems*, vol. 10, no. 4, pp. 1904-1926, 2016.
- [27] A. Albadarneh, I. Albadarneh and J. Alqatawna, “Iris recognition system for secure authentication based on texture and shape features”, *IEEE Jordan Conference on Applied Electrical Engineering and Computing Technologies (AEECT)*, pp. 1-6, 2015.
- [28] Wang, Zi & Li, Chengcheng & Shao, Huiru & Sun, Jiande, “Eye Recognition with Mixed Convolutional and Residual Network (MiCoRe-Net)”, *IEEE Access*. Vol. 14, No. 8, August 2015.
- [29] Himanshu Rai, Anamika Yadav, “Iris recognition using combined support vector machine and Hamming distance approach”, *Expert Systems with Applications*, Vol. 41, issue 2, pp. 588-593 2014.
- [30] Yung-Hui Li, Marios Savvides “An automatic iris occlusion estimation method based on high-dimensional density estimation” *IEEE transactions on pattern analysis and machine intelligence*, Vol. 35, no. 4, April 2013.
- [31] Parneet Kaur, Komal Sood “Facial-iris automatic multimodal biometric identification system using-cnn method”, *Journal of Emerging Technologies and Innovative Research (JETIR) April 2021, Vol. 8, issue 4.*
- [32] H Nair, S. Anu, P. Aruna and M. Vadivukarassi. “PCA BASED Image Fusion of Face and Iris Biometric Features”, *International Journal of Recent Advances in Engineering & Technology*, 2020.
- [33] Ammour, B.; Boubchir, L.; Bouden, T.; Ramdani, M. “Face-iris multimodal biometric identification system”, *Electronics MDPI* 2020.
- [34] Kagawade, Vishwanath & Angadi, Shanmukhappa “Fusion of frequency domain features of face and iris traits for person identification” *Journal of The Institution of Engineers (India)* 2020.
- [35] B. Ammour, T. Bouden and L. Boubchir, “Face-Iris Multimodal Biometric System Based on Hybrid Level Fusion”, *41st International Conference on Telecommunications and Signal Processing (TSP)*, pp. 1-5, 2018.
- [36] Md. Zahidur Rahman, Md. Hasan Hafizur, Rahman and Md. Mujibur Rahman Majumdar” Distinguishing a person by face and iris using fusion approach” *International Conference on Sustainable Technologies for Industry 4.0 (STI)*, 24-25 December, (Dhaka) 2019.
- [37] B. Ammour, T. Bouden and L. Boubchir, “Face-Iris Multimodal Biometric System Based on Hybrid Level Fusion”, *2018 41st International Conference on Telecommunications and Signal Processing (TSP)*, pp. 1-5, 2018.
- [38] Ammour, B. & Bouden, Toufik & Boubchir, Larbi, “Face-Iris Multimodal Biometric System using Multi-resolution Log-Gabor Filter with Spectral Regression Kernel Discriminant Analysis”, *The Institution of Engineering and Technology IET Biometrics*, pp 482-489, Vol. 7 Iss. 5 2018.
- [39] Y. Bouzouina and L. Hamami, “Multimodal biometric: Iris and face recognition based on feature selection of iris with GA and scores level fusion with SVM”, *2017 2nd International Conference on Bio-engineering for Smart Technologies (BioSMART)*, pp. 1-7 2017.
- [40] B Ammour, B. & Bouden, Toufik & Amira-Biad, Souad, “Multimodal biometric identification system based on the face and iris”, *2017 5th International Conference on Electrical Engineering - Boumerdes (ICEE-B)*, pp. 1-6, 2017.
- [41] Manasa G, Prathusha J S, Supriya Y N, Dr. Saritha Chakrasali, “Multimodal Biometrics-Feature Level Fusion of Face and Iris Biometrics”, *International Journal of Engineering Research & Technology (IJERT) ICIOT (Volume 4 – Issue 29)*, 2016.
- [42] Kirti V. Awalkar, Sanjay G. Kanade, Dattatray V. Jadhav, Pawan K. Ajmera “A multi-modal and multi-algorithmic biometric system combining iris and face” *International Conference on Information Processing (ICIP) Vishwakarma Institute of Technology*. Dec 16-19, 2015.
- [43] Guang Huo Yuanning Liu Xiaodong Zhu Hongxing Dong Fei He “Face-iris multimodal biometric scheme based on feature level fusion” *Journal of Electronic Imaging* Vol. 24(6) Nov/Dec 2015.
- [44] V. Azom, A. Adewumi and J. Tapamo, “Face and Iris biometrics person identification using hybrid fusion at feature and score-level”, *Pattern Recognition Association of South Africa and Robotics and Mechatronics International Conference (PRASA-RobMech)*, pp. 207-212, 2015.
- [45] Eskandari, Maryam and Önsen Toygar, “Fusion of face and iris biometrics using local and global feature extraction methods”, *Signal, Image and Video Processing* 8, 2014.
- [46] Sanjeevakumar M Hatture, Ashwini Gouripur, “Age Estimation of Person Based on Face Features”, *1st International Conference on Advances in Information Technology (ICAIT)*, pp.13-18, 2019.

[47] Sanjeevakumar M. Hatture Madhura Shettar, "A Model for Unconstrained Face Recognition", International Journal of Engineering Research & Technology, Vol.5, Iss 6, pp. 70 -73, 2017.

[48] Suvarna Nandyal Anita Kori, Swathi S. Wali, Sanjeevakumar M. Hatture" Antispoofing Methods for Authenticating Live Users in Biometric System", International Journal of Science and Research (IJSR), Vol.5, Iss 6, pp. 2694-2699, 2014.

[49] Sanjeevakumar M Hatture, PR Karchi, "Prevention of spoof attack in biometric system using liveness detection", Int. J. Latest Trends Eng. Technol, pp.42-49, 2013.

[50] S A Angadi, S M Hatture, V A Hiremani, "Real Time Face Recognition for user Authentication Using Color Local Texture Features", Proceedings of International Conference on Emerging Research in Computing, Information, Communication and Applications, pp. 715-721, 2013.

