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Multimodal Biometric Fusion Of Face-Iris In Person Recognition Framework

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ABSTRACT

Advancement of biometric frameworks in real-time applications contains mostly unimodal biometric frameworks, where the information gathered from single trait. There is chance that single traits do not recognize a person rightly because of existence of some limitations with modalities we choose. By making use of multiple biometric modalities using fusion operation, those limitations are overridden. In this paper, a novel multimodal biometric person recognition system is proposed, that is based on two fusion methodologies feature-level and score-level, which are compared comprehensively, for face and iris traits, in order to predict the methodology which gives higher recognition rates, to determine system's performance. We have identified four databases for face images and two databases for iris images and combined these in to eight groups of data sets for the experimentation, with four features extraction approaches such as GLCM, LBP, FD and PCA applied separately. The higher recognition rates are achieved for score-level fusion when used with the GLCM and LBP approaches, with the minimal EER and maximum accuracy. The performance of the proposed model is compared with existing multimodal face-iris biometric frameworks.

Keywords: Multimodal Biometric, Face-Iris, Fusion, Feature-Level, Score-Level

1. INTRODUCTION

Biometrics is natural and one-of-a-kind trademarks that distinguish people. Biometrics might be physiological as Face, DNA, Iris, and Fingerprints or characteristics as keystrokes, stride, and marks [1]. Recognition of Biometric has been developed expediently and is mostly utilized in our life every day. The biometric approaches identify and confirm the features precisely, quickly, and suitably to control the process of entry in dedicated frameworks or applications [2]. It is significant to control access and keep hackers from compromising or perceiving important templates. Biometrics used are separated into logical and physical features [3]. The physical features which are unique are characterized as iris,face, retina, finger-print and palm-print. However, the provisions which are called behavioural or logical features are estimated by action of the body and its response against the various conditions like signature, voice, walking style and keystrokes samples.

These biometric strategies estimated qualities or attributes of our human body, that are utilized to check that no hackers can access or control the admittance to functionalities delivered [4][5]. On the off chance that an intruder attempts to get to the framework and a piece of the private secret key is compromised, it might violate protection for many of the administrations [6]. Organizations anticipate keeping their records safe and further develop a service network to devote illicit admittance to them. Identification and validation are utilized to affirm that the approved entry could only get into the right and secure location. Authentication and authorization by customary procedures, explicitly passwords and Personal Identification Number (PIN), has been applied throughout the long term. These days, we have been making use of attractive cards and PINs for much security [7].At the point when an application needs a significant degree of protection, framework security isn't much reliable, hence features of biometric should be secured. This works on the privacy and precision in identification of people. Significant security properties have been accomplished by biometric-based validation procedures, explicitly in telemedicine administrations, to safeguard user data of passphrase attacks [8]. In traditional biometric ID and authorization methods, cross-coordinating and cross-application invariance are significant difficulties that make a hindrance towards these frameworks since all applications and services engaged with user's biometrics could be effectively hacked, so the data of userswould be followed easily [9], [10].

In remote frameworks used for surveillance, authentication methods required on IoT gadgets is crucial for IoT security since it takes part in preventing unapproved individual entry to IoT networks as illustrated in Figure 1, as foundation for fusion of two biometric modalities in proposed model. The model proposed focus on improving the rates recognitions for both face and iris modalities. Face and iris data sets are utilized in proposed model to extract required pictures and iris images to play out the pre-processing and for performance prediction. This paper intends to design a solid biometric framework by making fusion of face and iris attributes into one multimodal framework. In the interim, we have identified four databases for face images and two databases for iris images and combined these in to eight groups of data sets for the experimentation, with four features extraction approaches such as GLCM, LBP, FD and PCA applied separately. The higher recognition rates are achieved for score-level fusion when used with the GLCM and LBP approaches, with the minimal EER(Equal Error Rate) and maximum accuracy.

Biometric information is an intrigued verification way because of its benefits over old-way secret key based confirmation strategies. Although the security of biometric information itself is fundamental, the first biometric information can't be substituted or modified whenever compromised. Instances of the standard actual components utilized in IoT biometric confirmation frameworks are the face, iris, finger impression, RNA and palmprint biometrics. The decision of a particular trait has created by the need of the applied validation framework. For example, voice modalities are advantageous in Android gadgets in light of the fact that the cell phones' implicit set is delicate to vocal attributes. Iris and face modalities-based confirmation frameworks are the most impressive and normal attributes for client validation in IoT frameworks. Finger impression methodology comprises of explicit particulars. Thus, particulars give one of a kind spatial appropriation to every user. A few ventures have been applied computerized finger impression distinguishing proof frameworks for guarantying security and protection. Additionally, numerous business and common applications exploit fingerprints for confirmation. Face confirmation frameworks utilize the actual connection between the spatial conveyance of included characteristics, for example, nose and eyes on the grounds that the face traits have an undeniable degree of explicitness at different conditions [11].

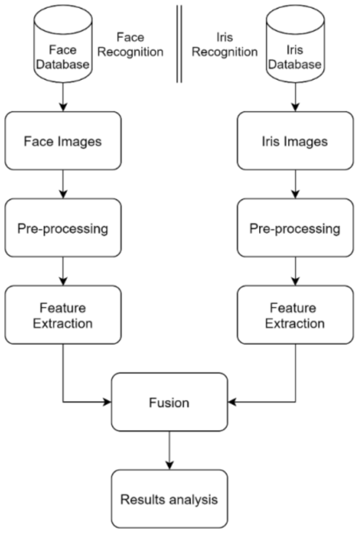

Figure 1: Working model of Face-Iris fusion

In this paper, an effective multimodal biometric person recognition system is proposed, that is based on feature-level and score-level fusion methodologies, for face and iris images of a person, with four features extraction approaches such as GLCM, LBP, FD and PCA, that are applied separately. The proposed recognition system relies on fusion models which extracts features and perform classification of the person without deploying any segmentation of images or techniques for detecting.

The authors [12] presented a validation framework for iris identifications. It depends on the blend of noninvertible changes and encryption for hiding the iris layout. They achieved a rate of detection 99%. In [13], diverse tools for security are introduced for face ID. They have utilized different activities for the extraction of mathematical components. Bio-convolving calculation was utilized to achieve both security and protection for the user's appearances. Researchers in [14] presented a validation system for multi-biometrics. It depends on consolidating different provisions of the biometric designs. Face recognitions was profoundly considered and several kinds of elements were given various degrees of recognition precision. Authors in paper [15] took on by consolidating numerous methodologies with feature choice techniques to pick the best set among them. Numerous methods depend on premasking windows to dispose higher and lower coefficients to upgrade performance. In any case, the issue lives in the shape and size of premask. To further develop discriminator capacity in discrete cosine, change space, authors in [16] utilized partial coefficients of the changed pictures with discrete cosine change to restrict the coefficients region for a superior performanceframework. Then, at that point from the chosenbands, utilized the segregation power analysis to look for the coefficients having the most elevated ability to separate various classes from one another.

The verifiable activities of innovations for recognitions of face trait, the current status of-the-art strategies, and directions required for the future activities are discussed. This will focus around the most recent informational indexes, 2D and 3D face ID strategies. Furthermore, this gives explicit thought to deep learning techniques as it depicts reality in those fields. The face ID utilizing DTCWT has been used satisfactorily for information base L-Spacek [17]. There are likewise approaches for parallel [18][19] implementation of different biometric characteristics utilized in sensitive applications for Internet of Things. The presentation of various characterization strategies and combination rules was examined by creator [20] with regards to multimodal and unimodal biometric frameworks using the MIT-BIH for electrocardiogram (ECG) information base and FVC2004 for unique finger impression data sets with 47 subjects from virtual multimodal data set. Performance of unimodal and multimodal frameworks is estimated utilizing beneficiary working trademark (ROC) bend and region under the ROC bend (AUC). The trial results demonstrated that AUC is 0.98 for consecutive multimodal framework and 0.95 for equal multimodal framework rather than the unimodal frameworks that accomplished just 0.95 and 0.87 for the ECG and finger-scandata bases, individually. The work done by authors [21] makes a thorough examination between two fusion techniques, feature level and score-level fusions, to figure out which strategy exceptionally further develops the general framework performance.

2. METHODOLOGY

This section details the two major multimodal biometric frameworks that have been developedand evaluated and comparisons of performances aredone to predict the bettermulti-feature model whichsatisfies higher accuracy with respect to all featureextraction methods. Four face and two iris datasetsare joinedto makeeightgroup of datasets, making use of four feature extraction methods such as GLCM, LBP, FD and PCA.The subject will be holding two face-iris biometric traits making use of relationship as one-to-one. Every database consists of 35 subjects, then the multimodal frameworkwould classify 280 subjects with single test picture and various no. of pictures for training, for eight group of datasets as illustrated below:

total subjects classified = face datasets (4) XIris datasets (2) X 35 (subjects/databases) =280

The Iris pictures arepre-processedwell before the application of feature extraction approaches. Processes such as localization of pupil and iris, and normalization of iris are carried out. Localization of Pupil make use of Connected Component Labelling Algorithm to identify region of pixel connected. At the end, application of four features extraction approaches [22] are donein order to extract the features of iris and generation of machine vectors. The Feature Extraction Approaches used in the methodologies are illustrated below.

Gray-Level Co-occurrence Matrix (GLCM): Work in various angles such as 0°, 45°, 90° and 135°, in whichevery direction denotes a particular relationship. Suppose directional info is not significant in feature extractions, four angles could be applied in equal manner without having any concerns. Depending on GLCM, several features such as energy, contrasts, entropy, correlation, homogeneity, autocorrelation,variance, and so on could be obtained [23]. Initiated by making countof particular intensity pairs along theparticular distanceand angles that are directionalupon sub-image. Outcomecould be Two-Directional matrix, with size beingtotal count of levels of intensity.

Example for the computation of GLCMconsideringthree (1,2, and 3)values gray level, angle 0 degree, and radius=1 is illustrated in Figure 2.

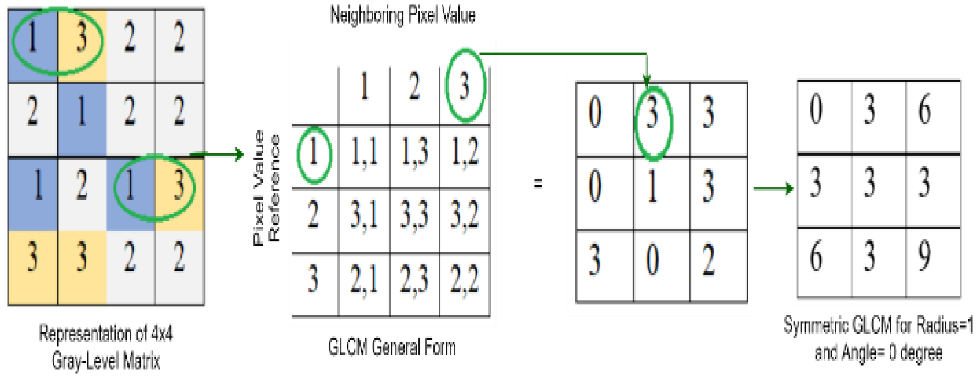

Figure 2: GLCM case for matrix of order 4 X 4

Local Binary Pattern (LBP): This operation is dependent on differences between threshold value and its 8 neighbours. LBP-code is equal to zero, if deference value is lower than zero; else, LBP-code is equal to one [24], LBP circle is prebuilt to generate a flexible count of k neighbours alongradius r. Operations of LBP are described using equations given in (1) and (2):

$$\mathrm{LBP}(\mathrm{k},\mathrm{r}) = \sum_{\mathrm{k}=0}^{\mathrm{k}-1} \mathrm{f}(\mathrm{GVk} - \mathrm{GVc}) \qquad (1)$$

$$\mathrm{f(y)} = \begin{cases} 1, & y \geq 0 \\ 0, & y < 0 \end{cases} \qquad (2)$$

In above equationsGVc is center pixel gray value andGVk is k neighbours gray value with values k = 0 andk − 1, where f is difference of pixel’s intensity in image. Output codes are categorizedtopatterns of kind uniform and nonuniform based on count of transitions amongbits 0s and 1s. Whereas patterns which are uniform has two benefits: it choosessignificant features such ascorners, lines, end edges, also it saves space by minimizinglength of code from 2^K to K(K − 1) + 3. Approach is better suitable for rotatingnoise-resistant andinvariant kind of image applications.

Fourier descriptors (FD) Approach: An advanced frequency-domain approach of Fourier transform, which used to analyzeimage shape, where analysed object is invariant to rotation, position, and scale change. The approach primarily provides the components as, DC thatpresentscoordinates x-y of centered point in border and radius of circle whichfixes border points. In order to implement FDs process,firstly, coordinates x-y of border must betransformed to complex nos. Secondly, signature of shape is made by calculating centroid distance utilizingequations (3), (4) and (5). At the end, Fourier coefficients are computed.

$$\mathrm{s(k)} = \mathrm{sqrt}((\mathrm{x(k)} - \mathrm{x_d})^2 + (\mathrm{y(k)} - \mathrm{y_d})^2) \qquad (3)$$

$$\mathrm{x_d} = \frac{1}{\mathrm{M}} \sum_{\mathrm{k}=0}^{\mathrm{M}-1} \mathrm{x(k)}$$

$$\mathrm{y_d} = \frac{1}{\mathrm{M}} \sum_{\mathrm{k}=0}^{\mathrm{M}-1} \mathrm{y(k)} (4)$$

$\mathrm{FD}_n = \frac{1}{M}\sum_{k=0}^{M-1} s(k) \exp\frac{-j2\pi nk}{M}$(5)

In above equations, coordinates (x_k, y_k) of M samples on boundary of region of images for k = 0, 1, 2. . ., M−1, (x_d , y_d) is region's center point , s(k) gives boundary shape described, FD_n is coefficient of Fourier transforms.

Principle Component Analysis (PCA) Approach: A mathematicalapproachwhich is based on calculatingmatrix covariance of feature vectors, also eigenvectors and eigenvalues. The approach is used forextraction of features and reducing the dimensions by maintaining significant features. where the dimension of the templates is reduced with maintaining the important features [25]. Mathematic model for calculation of PCA are provided in Equations (6), (7) and (8). Initially, computemean(P) for every image vector v_j.

$\mathrm{mean}(P) = \frac{1}{m}\sum_{j=1}^{m} v_j$(6)

Secondly, consider (x_j − X_j) (y_j− Y_j) be described as mean-centered image for every vector gotbysubtraction operation of image vector from mean of image, hencecalculate covariance matrix vectors Covusing teh equation described in (7).

$$\mathrm{Cov}(x, y) = \frac{\sum_{j=1}^{m}(x_j - X_j)(y_j - Y_j)}{m} \qquad (7)$$

X_j and $Y_j$providevalue of mean vector and two argumentsx$_j$and y_j are current values of x and y, and m is count of rows. Also, eigenvalues are computedout ofcov matrix as described using mathematical equation (8).

$$\det\left(\mathrm{Cov}_{(x,y)} - I\right) = 0 \qquad (8)$$

As a last step, for every eigenvalue λ, eigenvector V is computed as described in equation (9).

$$\left(\mathrm{Cov}_{(x,y)} - \lambda I\right)V = 0 \qquad (9)$$

A. Fusion Feature-Level

Fusion of modalities face and iris increasesreliability and stability ofperformance of identificationframeworkthrough the conversionofboth unimodal frameworks into single framework, termed as multimodal biometric framework. The block diagram given in Figure 3illustrates steps for fusion between features ofiris and faceby making use of four approaches of extraction of features such as GLCM, LBP, FD and PCA. Biometric system that is fused, is validated by using combination of eight datasets, that includes Spacek- CASIA_V3, Spacek- MMU_1, NI-CASIA_V3, NI- MMU_1, ORL- CASIA_V3, ORL- MMU_1, AR- CASIA_V3, AR- MMU_1.

Extraction of features of each modality are done separately, then the application of sequential rule is performed for the implementation of fusion mechanism, in which creation of concatenatedfeatures of face and iris is doneserially to generate a pattern for classification'sstage and conclude final decisions. The four frameworks of multimodal biometric depending on four approaches of feature extractions, are generated as illustrated in Figure 3. Sequential rule concept is described using a mathematical model in equation (10).

$\text{Fusion}_{fi} = \{A_{f1}, A_{f2} \ldots, A_{fm}, B_{i1}, B_{i2}, \ldots . B_{in}\}$(10)

A_{fm}representsthefeatures of facial with size of vector m and B_{in}represents the features of iris with size of vector n, provided the value of m and n are unequal.

B. Fusion Score-Level.

In this mechanism, which is generally used in multimodal biometric frameworks, results of recognitions are computed differently for every unimodal framework, afterward, score results of recognitions fused to ingle multimodal framework in order to improve the performance of the framework, which is illustrated in Figure 4. Initially, separate computation of score vectors belong to the process classification of both face and iris modalities are done and normalized as given in mathematical model of Equation (11) at lowest value of EER. In the second step, summation formula provided in Equation (12) is executed for fusing scores of face-irises [26]. In the final step, desired threshold which satisfies higher performance of fused framework is used to obtain decisions.

$$\text{SCORE}_j = \frac{\text{SCORE}_j - \text{MIN}_{scj}}{\text{MAX}_{scj} - \text{MIN}_{scj}} \qquad (11)$$

$$F_{scores} = \sum_{j}^{N} \left(\text{SCORE}_{fj} + \text{SCORE}_{rj}\right) \qquad (12)$$

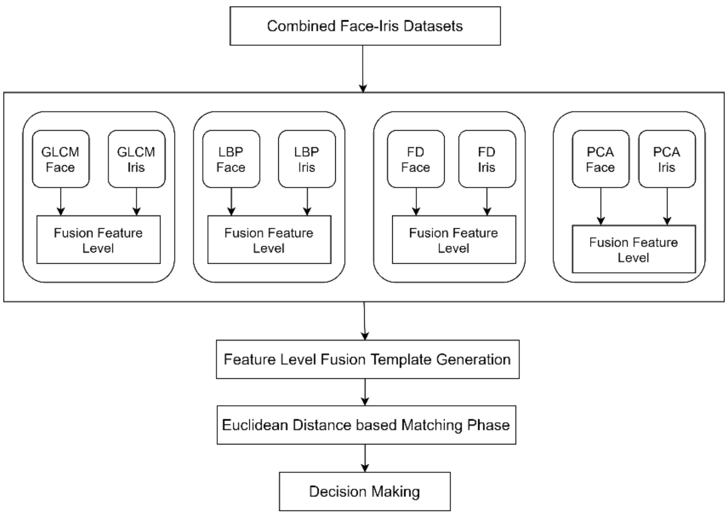

Figure 3: Feature-Level Mechanism based Multimodal Biometric System

SCORE_jdescribes normalization score of sample j of face - iris trait, MIN_{scj} and $\text{MAX}_{scj}$are lowest and highest values in score vector belong to sample j, relatively, SCORE_{fj} and SCORE_{rj} are score values of sample j of face-iris trait, accordingly, and Nrepresents count of biometric frameworkswhich have been utilised.

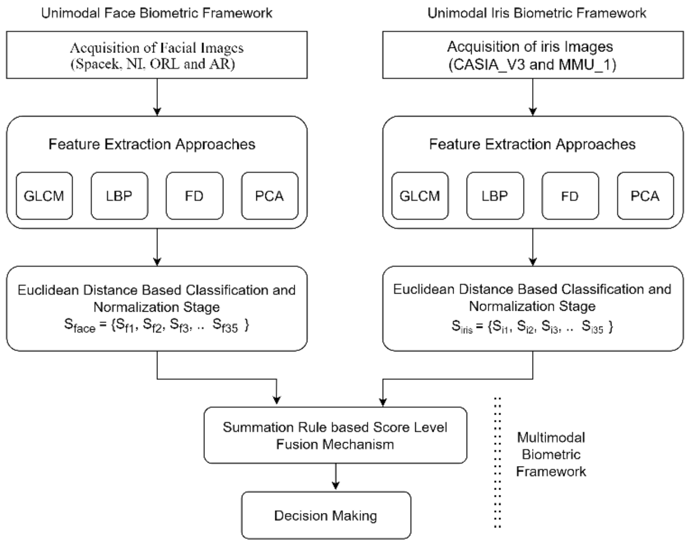

Figure 4: Score-Level Fusion Mechanism based Multimodal Biometric System

3. FACE AND IRIS DATASETS FOR EXPERIMENTATION

The data sets used for experimentation in our works are discussed in this section. There are four databases for face images and two databases for Iris images are identified.

Spacek Face database: Created by Libor Spacek [27] contains data of 395 individuals with 20 images per individual. There are 7900 images of both male and female genders of various racial origins. The Figure 5 shows face image samples of Spacek data sets.

Figure 5. Selected Sample of L- Spacek face pictures of human

Near Infrared (NI)Face Database:Contains varieties of expression, poses, scale, illuminations, blurring and combinations of all of them. The database [28] contains 115 humans and 15 pictures of every person. This standard database contains both male and female images with and without spectacles. The face images are of JPEG format with each image of size 768*576. The selected sample of Near infrared face pictures are shown in Figure 6.

Figure 6. Selected sample of Near Infrared face pictures

ORL (Olivetti Research Lab) database:This face database [29] consists of 400 pictures of size 112 x 92. This includes pictures of 40 persons, and 10 pictures for every person. The pictures were captured at numerous times, facial expressions and lighting. The faces are in a position of upright in frontal view, along with a slight left-right rotations. The selected sample of ORL face pictures are given in Figure 7.

Figure 7. Selected sample of ORL face pictures of human

AR Face Database:This includes 4,000 color images corresponding to 126 people. Images feature frontal view faces with numerous facial expressions, occlusions and illumination conditions. The pictures were taken at the CVC under strictly controlled conditions. No restrictions on wear, make-up, hair style, etc. were imposed to participants [30]. The sample images of AR face database given in Figure8.

Figure 8: Selected Sample of AR face pictures of human

CASIA iris data base [31] is broadly utilized by most of research experts. This presents barely any imperfections, and homogeneous qualities. CASIA-IrisV3 consists of 2655 pictures of iris comparing to 249 people; those pictures were captured with a resolution of 320 × 280 pixels. The Fig. 9 shows model pictures from the CASIA iris data base.

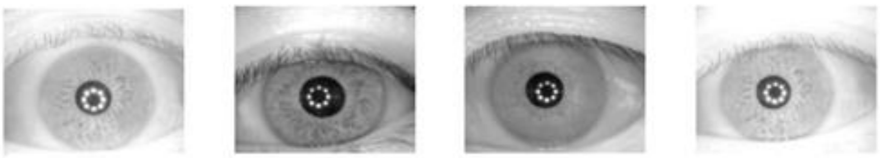

Fig.9: Iris images from CASIA

MMU-Iris-Database: Consists of both 5 close-up B/W images each of left and right eye of 46 persons, totally 460 pictures along with some of empty files. Every directory 'i' has folders left/right which carry 5 images each of both eyes for person 'k'. IRIS segmentation could be performed using Hough Circles/ Daugman's based segmentation or Transfer Learning. Samples given in Figure 10 contains both left and right eye images [32].

Figure 10:MMU1- Iris Images

4. RESULTS AND DISCUSSION

In this section results obtained from the experimentation of proposed model is discussed. The experimentation is done utilizing the Colab-Google Colaboratory framework, that is a ML based research tool which allows us to execute code in hosted CPU [33]. In order to implement the proposed model, Keras Python library [34] is used. The designed framework with multiple modalities is evaluated by using 4 feature extraction approaches and 8 groups of datasets, for 2 approaches of fusion of face and iris traits.The higher recognition rate is calculated by using Euclidian distance. The parameters for measuring performance such as False Acceptation Ratio (FAR), False Rejection Ratio (FRR), Equal Rejection Rate (ERR) and Accuracy rates are used for evaluations are defined below:

Let X be the Count of human faces/Iris accepted in database and Y be total count of humans available in database. Then,

$$\text{FAR} = \frac{X}{Y} \times 100 \quad (13)$$

Let P be the count of genuine humans rejected in database and Q be total count of humans in database. Then

$$\text{FRR} = \frac{P}{Q} \times 100 \quad (14)$$

$$\text{ERR} = \frac{(\text{FAR}+\text{FRR})}{2} \times 100 \quad (15)$$

$$\text{Accuracy Rate} = 100 - \frac{(\text{FAR}+\text{FRR})}{2} \quad (16)$$

Initially the unimodal experimentation was don for iris and face separately, by making use of the iris data sets and face datasets individually. The results were observed and analysed for accuracy. Then the multimodal model was prepared by fusing together the two traits face and iris. The results are illustrated below.

Table 1: Accuracy for Multimodal face-iris datasets (Spacek- CASIA_V3 and Spacek- MMU_1)

Face-Iris Datasets	Approaches	Accuracy Percentage	
		Fusion Feature-Level	Fusion Score-Level
Spacek-CASIA_V3	GLCM	86.60	87.88
	LBP	70.85	74.74
	FD	66.40	85.65
	PCA	72.44	73.20
Spacek- MMU_1	GLCM	70.56	86.44
	LBP	70.78	70.40
	FD	67.56	83.48
	PCA	69.26	75.92

Table 2: Accuracy for Multimodal face-iris datasets (NI- CASIA_V3 and NI- MMU_1)

Face-Iris Datasets	Approaches	Accuracy Percentage	
		Fusion Feature-Level	Fusion Score-Level
NI-CASIA_V3	GLCM	89.06	89.28
	LBP	72.85	76.47
	FD	68.10	87.77
	PCA	71.72	73.96
NI- MMU_1	GLCM	71.56	87.44
	LBP	71.88	71.38
	FD	68.36	84.62
	PCA	70.26	76.12

Table 3: Accuracy for Multimodal face-iris datasets (ORL- CASIA_V3 and ORL- MMU_1)

Face-Iris Datasets	Approaches	Accuracy Percentage	
		Fusion Feature-Level	Fusion Score-Level
ORL- CASIA_V3	GLCM	95.80	98.64
	LBP	96.60	96.86
	FD	98.35	98.65
	PCA	98.15	93.28
ORL- MMU_1	GLCM	74.98	84.64
	LBP	87.14	98.92
	FD	89.36	90.40
	PCA	96.80	98.70

Table 4: Accuracy for Multimodal face-iris datasets (AR- CASIA_V3 and AR- MMU_1)

Face-Iris Datasets	Approaches	Accuracy Percentage	
		Fusion Feature-Level	Fusion Score-Level
AR-CASIA_V3	GLCM	82.76	88.62
	LBP	96.26	98.65
	FD	78.84	80.65
	PCA	83.65	96.38
AR- MMU_1	GLCM	75.64	83.32
	LBP	93.42	98.84
	FD	71.30	73.28
	PCA	85.52	95.16

The computed accuracy values are recorded in Tables for various combinations of eight data sets. Table-1 presents the accuracy values for Multimodal face-iris datasets Spacek- CASIA_V3 and

Spacek- MMU_1 combination for all four approaches. It's found that GLCM approach records highest accuracy with Fusion Feature-level accuracy 86.40% and Fusion Score-Level accuracy 87.88% for Spacek- CASIA_V3. And with Spacek- MMU_1group, LBP provides better accuracy of 70.78% for Fusion Feature-level and GLCM gives 86.44% for Fusion Score-Level.Table-2 records the accuracy values datasets NI- CASIA_V3 and NI- MMU_1 combination for all four approaches. It's found that GLCM approach records highest accuracy with Fusion Feature-level accuracy 89.06% and Fusion Score-Level accuracy 89.28% for NI- CASIA_V3. And with NI- MMU_1 group, LBP provides better accuracy of 71.88% for Fusion Feature-level and GLCM gives 87.44% for Fusion Score-Level.

Table-3 records the accuracy values datasets ORL- CASIA_V3 and ORL- MMU_1 combination for all four approaches. Here, FD approach records highest accuracy with Fusion Feature-level accuracy 98.35% and Fusion Score-Level accuracy 98.65% for ORL- CASIA_V3. And with ORL- MMU_1 group, PCA provides better accuracy of 96.80% for Fusion Feature-level and LBP gives 98.92% for Fusion Score-Level.Table-4 records the accuracy values datasets AR- CASIA_V3 and AR- MMU_1 combination for all four approaches. LBP approach records highest accuracy 96.26% with Fusion Feature-level and Fusion Score-Level accuracy 98.65% for AR- CASIA_V3. And with AR- MMU_1 group, LBP provides better accuracy of 93.42% for Fusion Feature-level and 98.84% for Fusion Score-Level.It's observed that combined datasets satisfied higher recognition rates for both feature-level and score-level fusion using various feature extraction approaches. Comparing all the approaches, fusion score-level and LBP and GLCM approaches obtains much stable and maximum performance for recognition of face-iris modalities in proposed multimodal framework. The graphical analysis of accuracies of all the eight dataset groups for both feature-level and score-level fusions, utilizing four approaches, are illustrated in graphs depicted from Figure 11 through Figure 18.

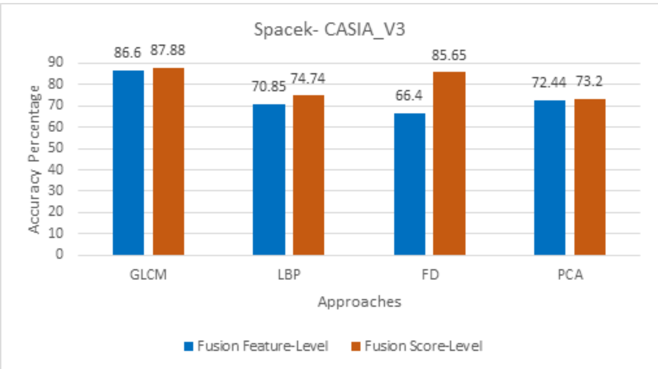

Figure 11: Accuracy Analysis of Feature-Level and Score-Level using Spacek-CASIA_V3 datasets

The behavioural factors such as FAR, EER, FRR, and also threshold for overall higher recognitions accuracies satisfied by approaches GLCM and LBP are analysed. The maximum performance competition is reflected among two fusion methodologies and 4 approaches of features extraction which are implemented making use of group of datasets ORL-CASIA_V3. Also, its observed that, the fusion score-level has performed better in many cases compared to fusion feature-level. Out of 32 levels of experimentations with four approaches and eight groups of datasets, the fusion score-level proved highest recognition rates for 30 levels. This shows that fusion score-level performs better in proposed multimodal biometric recognitions.

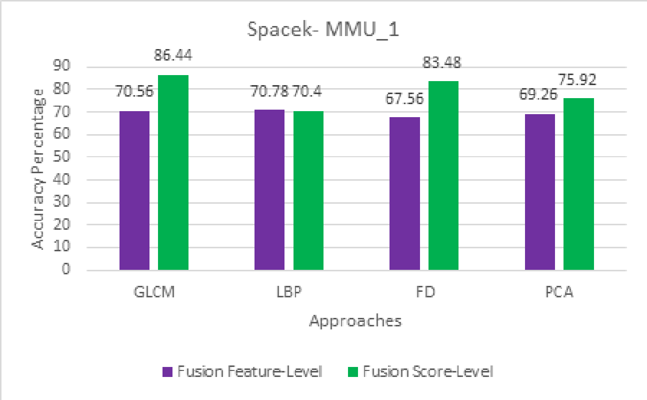

Figure **12:** Accuracy Analysis of Feature-Level and Score-Level using Spacek-MMU_1 dataset

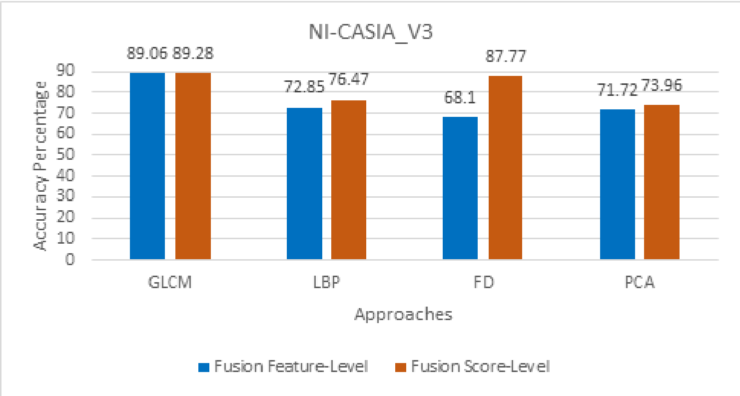

Figure 13: Accuracy Analysis of Feature-Level and Score-Level using NI-CASIA_V3 dataset

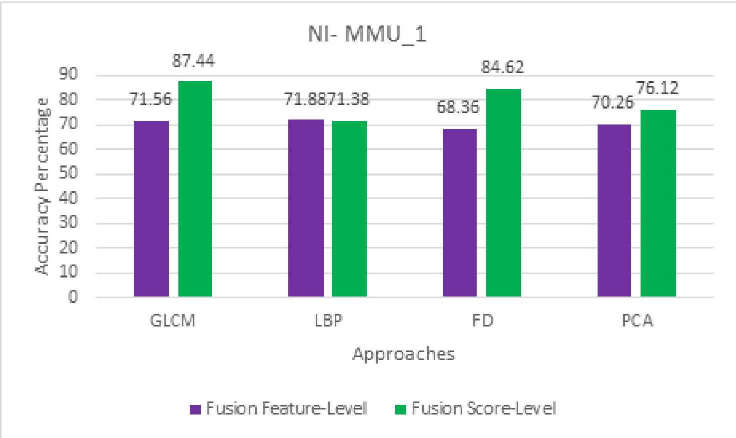

Figure 14: Accuracy Analysis of Feature-Level and Score-Level using NI-MMU_1 dataset

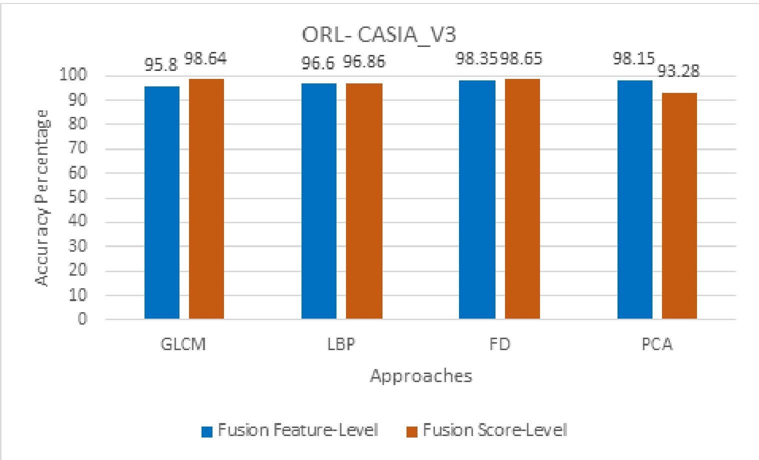

Figure 15: Accuracy Analysis of Feature-Level and Score-Level using ORL-CASIA_V3 dataset

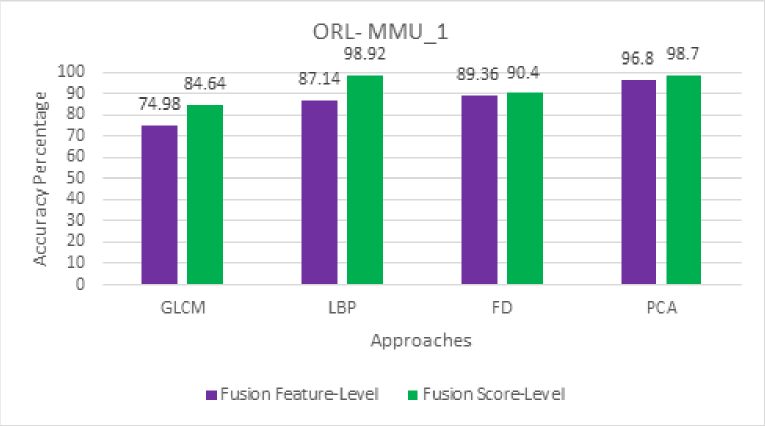

Figure 16: Accuracy Analysis of Feature-Level and Score-Level using ORL-MMU_1 dataset

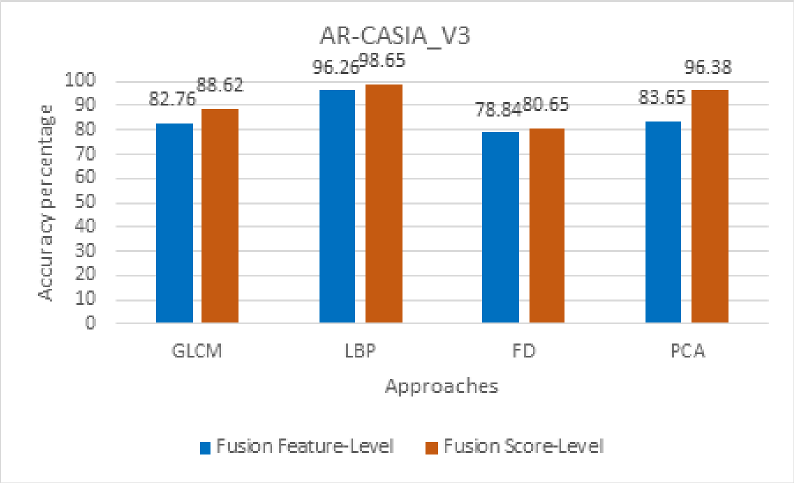

Figure 17: Accuracy Analysis of Feature-Level and Score-Level using AR-CASIA_V3 dataset

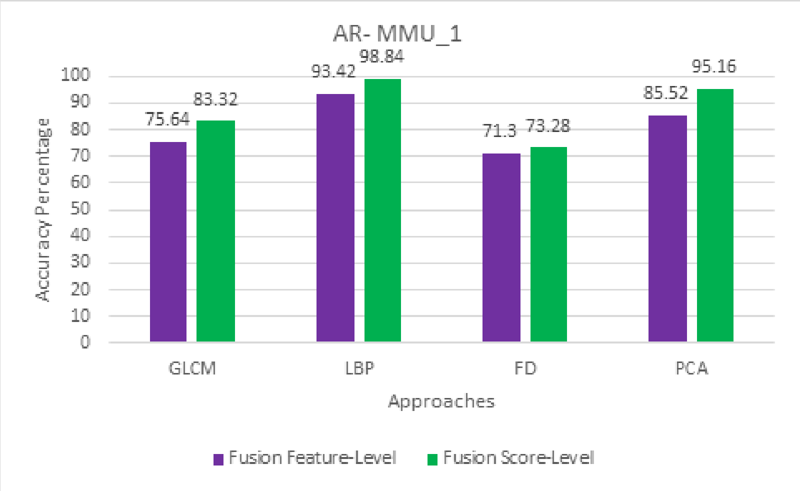

Figure 18: Accuracy Analysis of Feature-Level and Score-Level using AR-MMU_1 dataset

Discussions of Results: The results of recognition accuracy of experiments conducted are tabulated and analysed graphically above, using various approaches. Results illustrates that high accuracy obtained by the multimodal biometric system by fusion of both iris and face modalities, compared to those of unimodal systems. In the proposed model, maximum accuracy of 98.92% is achieved in score-level fusion model using Local Binary Pattern (LBP) approach, and 98.35% accuracy achieved in feature level fusion model using Fourier Descriptors (FD) approach. The Table-5 analyses the comparative results of existing models and the proposed model. The results demonstrate the superior position of the proposed model to the other multimodal biometric frameworks.

Table-5: Comparisons with Existing researches

	Modalities	Fusion Level	Accuracy %
[35]	Iris, Face	Score Level	98.20
[36]	Face, Iris	Feature Level	97.85
[37]	Face-Iris	Feature Level	98.25
[38]	Face-Iris	Feature Level	98.10
		Score Level	97.75
Proposed Model	Face Iris	Feature Level	98.35
		Score Level	98.92

5. CONCLUSIONS

The experimentation and the analysis done in this paper proved that the multimodal biometric frameworks would improve the robustness and safety. The research done encouraged to have fusion of multiple unimodal biometric traits to improve the reliability of the systems by choosing different feature extraction methodologies. We have discussed score-level and feature level fusion strategies for multimodal frameworks using face and iris as biometric traits. The research is done by making use of four approaches for features extraction such as GLCM, LBP, FD and PCA applied separately for eight groups datasets from four face databases and two iris databases, which includes Spacek-CASIA_V3, Spacek- MMU_1, NI-CASIA_V3, NI- MMU_1, ORL- CASIA_V3, ORL- MMU_1, AR- CASIA_V3, and AR- MMU_1. The accuracy is calculated for all the approaches in both fusion strategies. It's observed that, the higher recognition rates are achieved for score-level fusion when used with the GLCM and LBP approaches, with the minimal EER and maximum accuracy. The False Acceptance Rates and False Rejection Rates were computed accordingly. The performance of proposed model is compared with the previous multimodal biometric frameworks.

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