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Multimodal biometric system based on fusion techniques: a review

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ABSTRACT
Biometric allude to an automatic procedure of acknowledging an individual utilizing their behavioral or physical characteristics. The biometric framework, which utilizes one cue for authentication is termed as unimodal biometric. The unimodal biometric framework confronts numerous snags like dearth of distinctiveness, universality intra-class similarity and multimodal biometric is one of best options to conquer these issues, which is a framework that utilizes two or more cues for authentication. This study presents the overview of multimodal biometric recognition systems. Multimodal biometric recognition systems augment the security and concealment of digital information. From last two decades, there are a lot of research work on information fusion. We have discussed recent trends in multimodal biometric depending upon the type of fusion scheme and the level of fusion i.e. sensor level or feature level fusion, decision level fusion, score level fusion and hybrid fusion level. The types of fusion are conversed in detail with their individual merits and demerits. In addition to that, the methodologies, employed databases and accuracy results of the existing works are presented to showcase the profound usage of multimodal biometric design. The paper is targeted toward presenting a comprehensive review of different fusion schemes in combining various biometric modalities.

KEYWORDS
Information security; biometric recognition; multimodal biometric; information fusion

1. Introduction

Biometric is an automatic procedure of recognizing an individual utilizing their behavioral or physical characteristics like palm-prints, fingerprints (R. Gupta et al., 2020), voice, finger vein, ECG, or iris (Bowyer et al., 2010; Jain et al., 2011). These characteristics are stated as biometric traits, cues or modalities. In course of recent years various different biometric cues (Abozaid et al., 2018; Z. Ali et al., 2018; Ammour et al., 2018) have been investigated for various applications going from individual gadgets to outskirt control frameworks (Anil Kumar, 2005). The reputation of biometrics in authenticating frameworks is growing progressively as the biometric cues like iris((Kapoor et al., 2019; Dua et al., 2019), palm-print, periocular are everlasting, less susceptible to fraudulent attacks (Fumera et al., n.d.) and cannot be disremembered like PIN and passwords (Fenker et al., 2012). Unimodal biometric framework has many snags like susceptibility to noise, prone to spoof attacks (Maiorana et al., 2014), less compatibility, interclass resemblance and intra-class deviations. To mitigate these snags of unimodal biometric framework and to achieve robust biometric framework with augmented authentication rate more than one cue can be utilized simultaneously (Bowyer et al., 2006; K. I. Chang et al., 2006).

So, to utilize more than one cue simultaneously in a biometric framework the type of fusion strategy applied plays a vital role (Dehaqi, 2019; Damer et al., 2019; Drozdowski et al., 2020). The categorization of fusion process can be done as sensor or sample level fusion (uniting samples from multiple sources), feature level fusion (pooling features acquired from different cues), score level fusion (uniting genuine and imposter scores of multiple cues), rank level fusion (uniting ranks of multiple cues), hybrid level fusion (utilizing more than one fusion strategy)(Verma, 2018).The biometric framework which utilizes one cue for authentication is termed as unimodal biometric recognition framework, but there are numerous downsides of this framework. As it is very tough to fraudulent the robust system with multiple cues, so multimodal framework (Zhong et al., 2019; Smith-creasey et al.,

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n.d.; Kathed et al., 2019; Bianco & Napoletano, 2020; Choudhary, 2019) is the best solution for these issues in which two or more cues are utilized for authentication. The general multimodal biometric authentication framework is summarized in Figure 1.

However, depending upon the kind of application where the framework is to be utilized, cues can be chosen. There are five schemes for information fusion (R. Singh et al., 2016; Oloyede et al., 2016) in the literature: data or sensor level fusion, score level fusion, feature level fusion (Khade, 2019), decision level fusion and rank level fusion (Bowyer et al., 2006). Furthermore, hybrid fusion (Peralta et al., 2016) is also discussed in the related work. Fusion of multiple cues has been demonstrated to be beneficial in various applications (Singla, 2019). Fusion of various biometric modalities has been investigated at different fusion levels (Barra et al., 2016; Akulwar, 2019). Sensor level fusion involves integrating various samples of crude information acquired by utilizing various sensors or a similar sensor (Chattopadhyay et al., 2015). Feature level fusion (Algashaam et al., 2018) alludes to an integration of feature vectors acquired using multiple cues to create another feature vector. Score level fusion (Nigam et al., 2015) integrates the matching scores produced through different classifiers to reach upon the concluding result in terms of authentication.

Moreover, decision level fusion fuses the decisions provided by different matching modules to reach at the final authentication decision. Rank level fusion consolidates (Jemaa et al., 2016) various ranks related to every template in dataset, where different biometric authentication techniques are used to figure every position. As score level (Zafar et al., 2017) (Sabharwal & Gupta, 2019) combination has numerous focal points when contrasted with other level fusion techniques. Fusion at score level is prone to contribute better authentication accuracy as it contains progressively placated data, which are both attainable and practical (Guo et al., 2019). Following are the advantages of multimodal biometric framework over unimodal biometric framework (Mane & Jadhav, 2009; S. Kumar et al., 2018):

Augmented accuracy-The outcomes obtained from numerous cues can be fused by choosing the suitable level of fusion and applying efficient fusion scheme to achieve augmented accuracy.

Additional universality-Multimodal biometric framework can counter the non-universality issue of unimodal biometric framework. For example, identification of someone is still feasible by using the other cue even if due to some ailment, he is incapable to access palm-print framework.

Easy accessibility-As there is flexibility in accessing multimodal framework by using any cue, it is more convenient for user to access the same in comparison to unimodal framework.

Reduced vulnerability to spoof attacks-Concurrently spoofing more than one cue is very challenging so the multimodal frameworks are less prone to fraudulent attacks.

There are two phases in a biometric framework (S. Kumar et al., 2018) i.e. enrollment phase and verification phase. In enrollment phase the acquired cues are stored in the database in binary form. These binary versions of biometric cues are known as biometric templates and these epitomize the connection among user and identity. In order to verify the authenticity of a particular user, these templates are matched with the claimed identity at verification stage. There are several categories of fraudulent attacks on the templates stored in the database like spoof attack, hill climbing attack, torzan horse attack. Protecting templates of users in

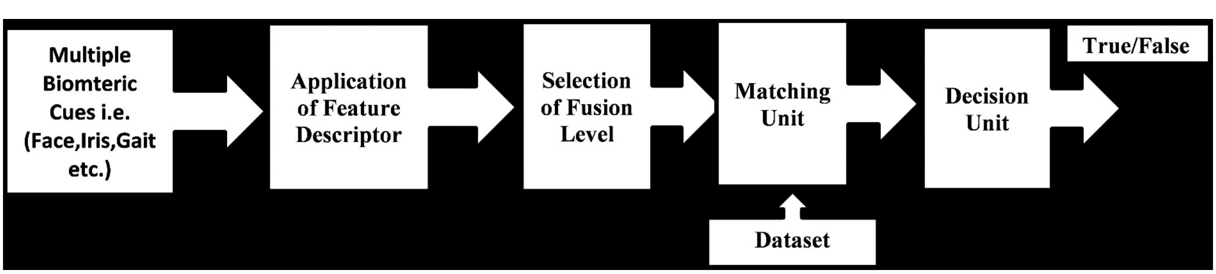

Figure 1. The general multimodal biometric authentication framework (Arun et al., 2006).

multimodal biometric is significant and tedious task as templates can be stolen to access secured framework fraudulently. Template transformation and biometric cryptosystem can provide security to the templates. In template transformation, the templates are modified using a cryptographic key. In biometric cryptosystem the enrolled template is transformed into a sketch, and then this sketch is stored in the database as without biometric data of genuine user it is not feasible to obtain the template from a drawn sketch.

Furthermore, fuzzy vault (Sree, 2016; Vinothkanna, 2020) is also a renowned approach to protect the templates in the database. So using these strategies even if the templates are stolen from the database, these cannot be utilized for accessing a secured framework. Due to robustness and lesser vulnerability to spoof attacks or fraudulent calls, the multimodal biometric frameworks seek a wide range of application area (Fumera, Marcialis, Biggio, Roli & Schuckers, 2014). The selection of a multimodal biometric framework can be done on the basis of level of security to be provided for a particular application. The multimodal biometric framework with lesser FAR and higher FRR seeks its application in providing security to the sensitive places like accessing bank accounts and secured buildings. In providing security to lesser sensitive applications; like access to classrooms, transport and offices the multimodal biometric frameworks with lesser FRR and higher FAR can be utilized. In defense, border is managed by utilizing automated multilevel security frameworks for identification of criminals and fraudulent attacks .

However, forensic and intelligence investigation department promotes quick, robust and highly accurate multimodal framework to recognize the criminals on the basis of acquired data from prior endeavors done by them. Additionally, in this digital world all the purchases and sales of things take place in online mode so the access to the personal gadgets also needs higher level security (Dahea & Fadewar, 2018). Enterprises and business trades also seek multimodal biometric security with certain properties like less computation complexity, cost effectiveness, consumer friendly interface. So a multimodal biometric is the prerequisite in every arena in which high level of security is essential (M. Singh et al., 2019).

The main objective of this work is to give an overview of multimodal biometrics systems and the multimodal biometric databases available for research. The rigorous review of multimodal biometric databases is also presented in this work with number of traits, number of participants, number of images, capturing device used, year of release of database, acquisition environment of each database. Additionally, we have presented the sample images of various datasets wherever possible. We classified our work on the basis of schemes of fusion of traits. The types of fusion are conversed in detail with their individual merits and demerits. In addition to that, the methodologies, employed databases and accuracy results of the existing works are presented to showcase the profound usage of multimodal biometric design.

The objective of this review is to answer the following research queries:

Research Query1: How many levels of fusion are there to fuse multiple traits?

Research Query2: What are the most popular levels of fusion?

Research Query3: What are the existing multimodal databases?

Research Query4: What is cancelable multimodal biometric?

Research Query5: What are the vulnerabilities of multimodal biometric?

Research Query5: What are the Challenges in multimodal biometric systems?

Research Query6: What are the future directions in the area of multimodal biometric systems?

The organization of rest of this article is as follows. Section 2 provides description of preliminaries; Section 3 offers a depiction of literature review which is categorized into eight subsections on the basis of fusion strategies employed. In Section 4, we present the cancelable multimodal biometric systems. Section 5, provides details of existing databases with their sample images. In Section 6, we discuss vulnerability of multimodal biometric system to spoof attacks. In Section 7, we provide future direction for researchers. In Section 8, we conclude the proposed work.

2. Preliminaries

In this section, some elementary information is provided which would be repeatedly used in this article.

2.1. Evaluation metrics

This section is dedicated to the definitions of performance metrics, which are given as follows (Vyas et al., 2016):

FAR: False acceptance rate is defined as the probability of giving access to a secured system to a non-authorized person erroneously. Statistically, it can be epitomized as:

$$FAR = \frac{false\_accept(\eta)}{length(imposter\_score)} \tag{1}$$

FRR: False rejection rate is defined as the possibility to reject incorrectly an authorized person to access the system. Statistically, it can be epitomized as:

$$FRR = \frac{false\_reject(\eta)}{length(genuine\_score)} \tag{2}$$

EER: Equal error rate can be stated as the intersecting point between the curves of FAR and FRR.

$$EER = \frac{FAR(\eta_1) + FRR(\eta_1)}{2}. \tag{3}$$

GAR: At a threshold at which the values of FAR and FRR are equal, the percentage of genuinely accepted persons is defines as genuine acceptance rate. Statistically it can be epitomized as:

$$GAR = 1 - FRR(\eta_1). \tag{4}$$

DI: The extent of separation between genuine and imposter class is measured using decidability index. Statistically, it can be epitomized as:

$$DI = \frac{\left|\mu_g\right| - \left|\mu_i\right|}{\sqrt{\sigma_g^2 + \sigma_i^2}} \tag{5}$$

Where η is the threshold at which FAR and FRR are measured, $\eta_1$is the threshold at which FAR and FRR are equal. Andσ_g,σ_i,μ_g and μ_i are the standard deviations of genuine and imposter class, respectively. Imposter scores less than η and genuine scores greater than η are represented by false_accept (η) and false_reject (η), respectively.

2.2. Biometric fusion

Fusion scheme plays a vital role in augmenting the performance of multimodal framework (Jain et al., 2005; D. Chang et al., 2021). The selection of effective fusion scheme to fuse the evidences acquired from multiples cues is the backbone of an efficacious multimodal biometric framework (Ma et al., 2020; Saeed et al., 2020). There are five schemes for information fusion in the literature, specifically data or sensor level fusion, score level fusion (Sharma et al., 2018; Kacar & Kirci, 2018; Soviany & Pu, 2019), feature level fusion (Setumin et al., 2020; Jiang et al., 2020; Dahea, 2020; Kaur et al., 2017), score level (Ghayoumi, 2015), decision level fusion and rank level fusion (Truong, et al., 2020; Tumpa & Gavrilova, 2020). Furthermore, hybrid fusion is also discussed in the related work. Fusion of multiple cues has been demonstrated to be advantageous in various applications (Di et al., 2020; Singh, 2018). Fusion of various biometric modalities has been investigated at different fusion levels (Choudhary, 2019). Fusion at score level is prone to contribute better authentication accuracy as it contains progressively placated data, which is both attainable and practical. Multiple levels of fusion are defined below:

(i) **Sensor-level fusion** or data-level fusion in general stated as multi instance-algorithm, in which biometric information is integrated instantly after its procurement (J. Wang et al., 2008; Kisku & Tistarelli, 2009; Kisku & Tistarelli, 2009). That is, raw data acquired from different or same sensors are fused before application of feature descriptors (Gad, El-latif, Elseuofi, Ibrahim, Elmezain & Said, 2019). For sensor level fusion, there should be more than one instance of each identity. For instance, in case of facial multimodal biometric system, multiple images of face taken from different angles utilizing one sensor or multiple sensors should be integrated to frame out one outcome (Kusuma & Chua, 2011; Chitroub et al., 2012; Chitroub et al., 2012). Then, the final outcome is contrasted with the sample to be authenticated. It is significant that the information to be combined ought to be similar, for example, the images acquired from different sensors must be of same resolution (Chattopadhyay et al., 2015; Sujatha & Chilambuchelvan, 2017). But, sensor-level fusion cannot be regarded as an universally accepted fusion scheme as most of the times, it is very hard to fuse the modalities of interest at the sensor level (P. Chen et al., 2019; Khan, 2019). The general multimodal biometric authentication framework with sensor level fusion is summarized in Figure 2.

(ii) **Feature-level fusion** alludes to an integration of feature vectors acquired using multiple cues to create another feature vector (Ross & Govindarajan, 2004). The features of multiple cues are extracted using feature descriptors like Linear Discriminant Analysis (LDA), DAISY, BRIEF, IOLD, HOG etc.(S. Kaur & Sharma, 2016; Sarangi et al., 2018). Then features acquired from every cue is concatenated to form a larger feature vector (Arashloo, 2015). And this resultant feature vector is matched with templates stored in the database to reach a final decision of authentication. The general multimodal biometric authentication framework with feature level fusion is summarized in Figure 3.

(iii) Score-level fusion alludes to the procedures where multiple matchers provides respective match scores after matching with templates stored in databases and then these scores are integrated together to reach upon the final conclusion of authentication (Jillela & Ross, 2012). The score-level fusion is the most common approach, as it does not involve any prior information about the features and classifiers (Nguyen et al., 2015; Liang et al., 2015; Imran, Supreetha et al., n.d.). However, it is only effective when the scores from two or more modalities fall in the same range (Sobabe, 2019). Otherwise, the errors caused by the normalization of scores may lead to loss of information, eventually resulting in poor accuracies. The general multimodal biometric authentication framework with score level fusion is summarized in Figure 4.

(iv) Rank-Level fusion is carried out after matching the input information sample with stored templates in the datasets of system (Anand et al., n.d.). The rank level fusion (Sing et al., 2018) is commonly embraced for identification not for verification mode of authentication. In verification there is one by one matching, as sample is matched with requested template kept in the dataset or record. Ranks are produced for every identity in terms of all the cues, then these ranks in terms of different modalities are fused for each identity (Hossein & Gavrilova, 2015). Identity with minimum score is considered as genuine identity

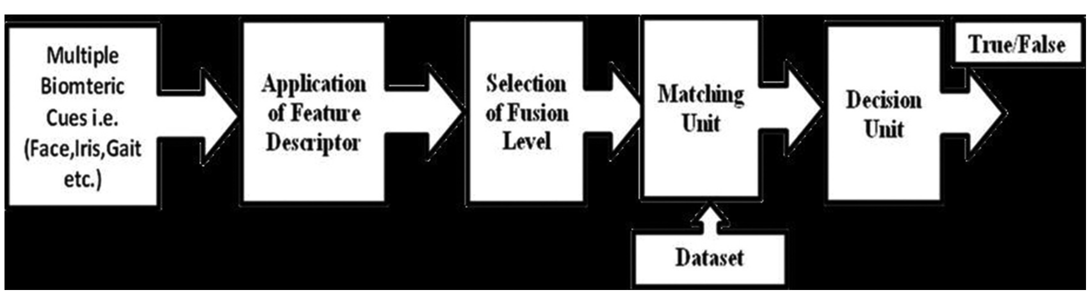

Figure 2. The general multimodal biometric framework with sensor level fusion(Arun et al., 2006).

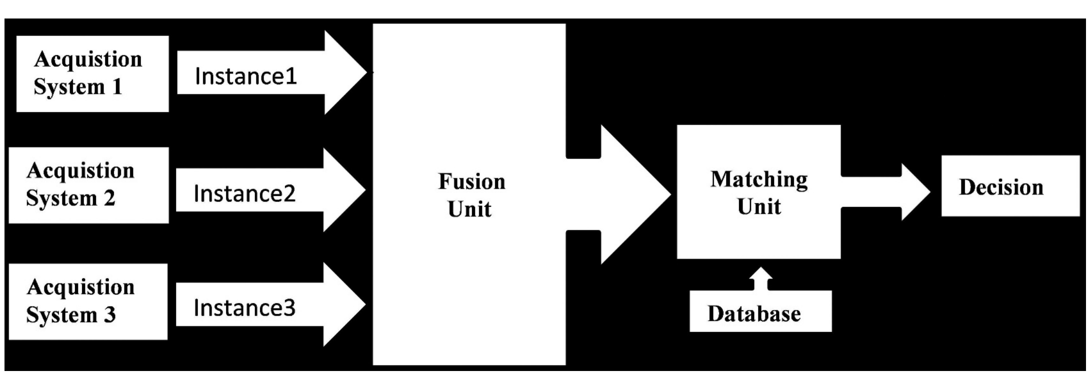

Figure 3. The general multimodal biometric framework with feature level fusion (Arun et al., 2006).

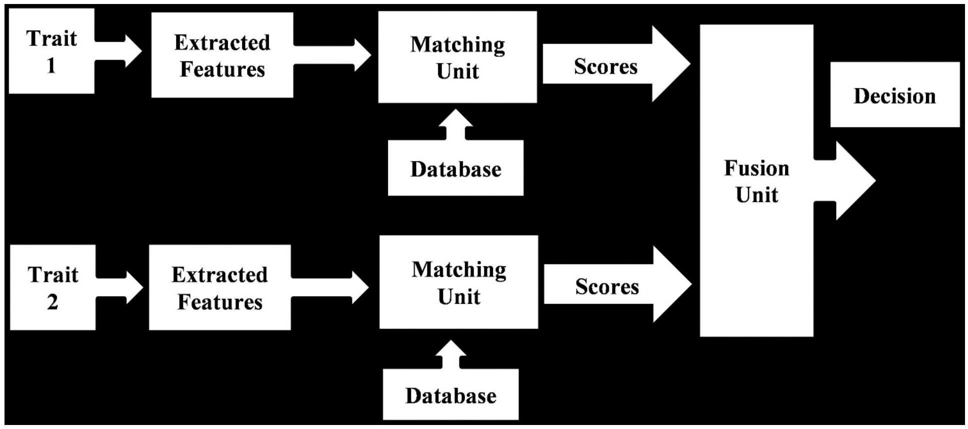

Figure 4. The general multimodal biometric framework with score level fusion (Arun et al., 2006).

(Elhoseny et al., 2018). This method offers better results however the information for fusion provided by it is very less. The general multimodal biometric authentication framework with rank level fusion is summarized in Figure 5.

(v) Decision-level fusion alludes to the procedures, in which integration is accomplished at the final stage i.e. decision level (Prabhakar & Jain, 2002)(Li, Hu, Pieprzyk & Susilo, 2015). Decision of individual matcher of unimodal biometric system are integrated to obtain conclusive result of authentication using techniques like Bayesian decision OR rule, AND rule, Majority voting, Decision table etc. As decision level fusion (X. Wang & Feng, 2019)(Devi, 2020) is performed after the decision has been made by different classifiers, it is very sensitive to individual classifier accuracy, which may cause erroneous decisions or biased decisions (Veeramachaneni et al., 2008). The general multimodal biometric authentication framework with decision level fusion is summarized in Figure 6.

3. Literature survey

Multimodal biometric systems and fusion techniques have been studied from decades. An extensive overview of the field of Multimodal biometric system is presented. The literature survey has been classified in six sections depending upon the techniques applied for fusion of multiple cues i.e. (1) fusion of samples (2) fusion of features (3) fusion of scores (4) fusion of ranks (5) fusion of decisions (6) fusion of features and decisions (7) fusion of scores and decisions (8) fusion of features, scores and decisions.

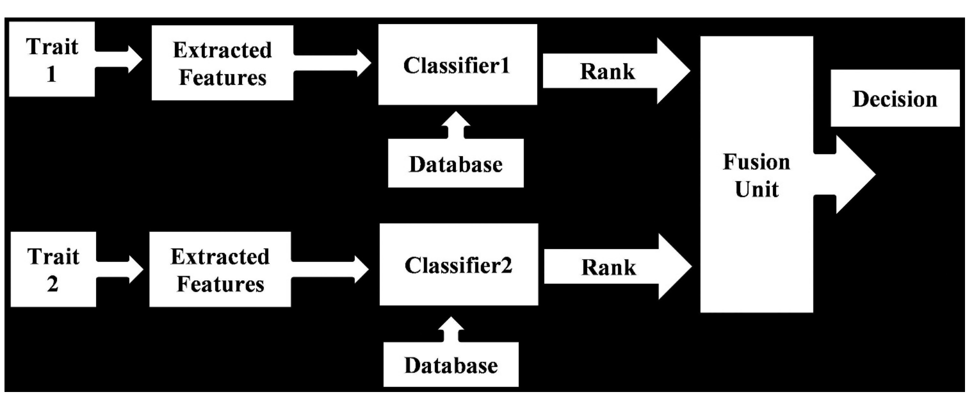

Figure 5. The general multimodal biometric framework with rank level fusion (Arun et al., 2006).

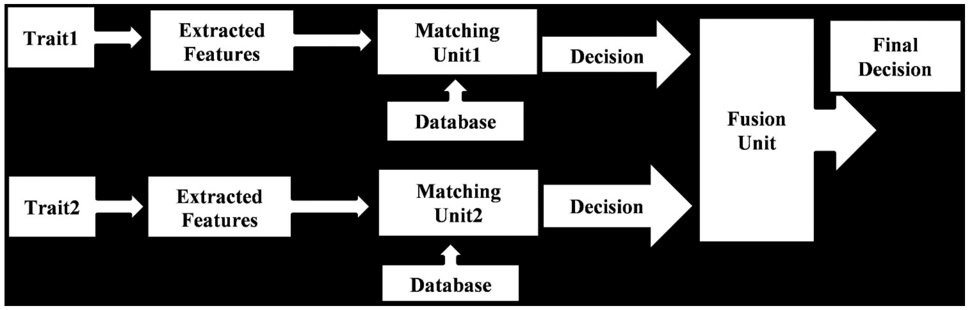

Figure 6. The general multimodal biometric framework with decision level fusion (Arun et al., 2006).

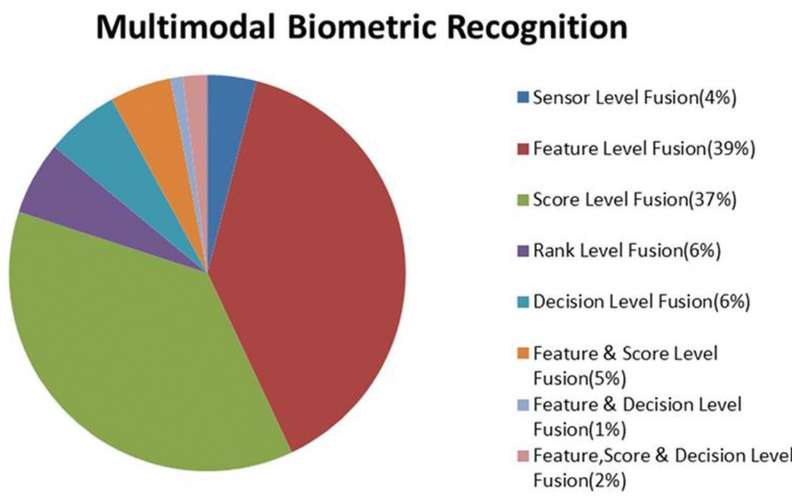

Figure 7. Pie chart showing proportions of reviewed articles.

Figure 8. Sample images from BT-DAVID multimodal biometric database (Chibelush et al., 1996).

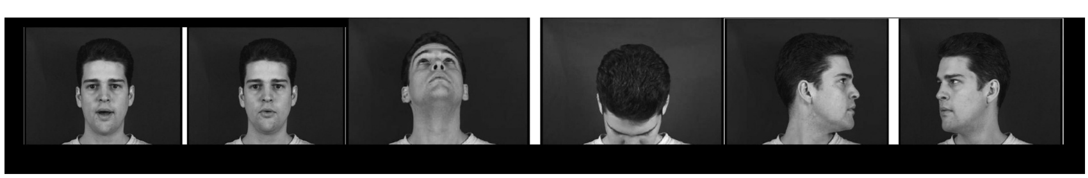

Figure 9. Sample images from XM2VTS multimodal biometric database (Messer et al., 2016).

3.1. Fusion of samples

(Wang et al., 2008) suggested the fusion of samples of palm-print and palm-vein using laplacian and wavelet based scheme to obtain the augmented recognition. They have authenticated their work on their own dataset with GAR = 99.7%. (Kisku & Tistarelli, 2009) fused face and palm-print using wavelets and SIFT operator for decomposition of images and extracting features respectively. They have approved their work on

Figure 10. Sample images from SMARTKOM multimodal biometric database (Steininger et al., 2002).

Figure 11. Sample images from BIOMET multimodal biometric database (Garcia-salicetti et al., 2003).

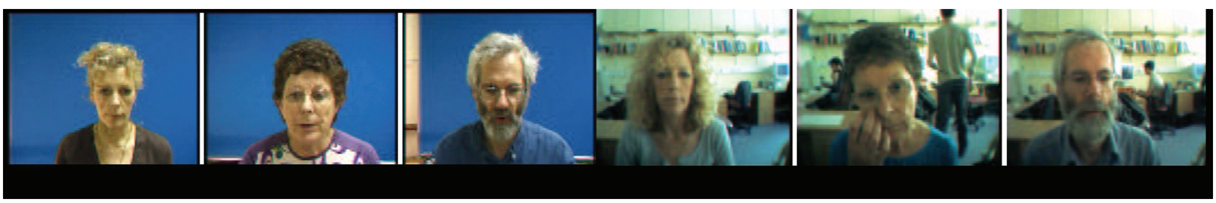

Figure 12. Sample images from BANCA multimodal biometric database (Hamouz & Popovici, 2003).

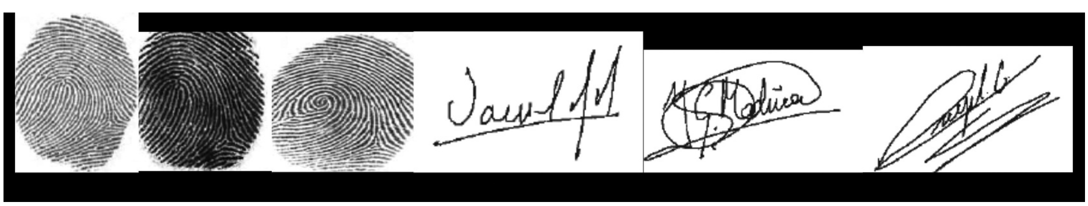

Figure 13. Sample images from MCYT multimodal biometric database (Simon et al., 2003).

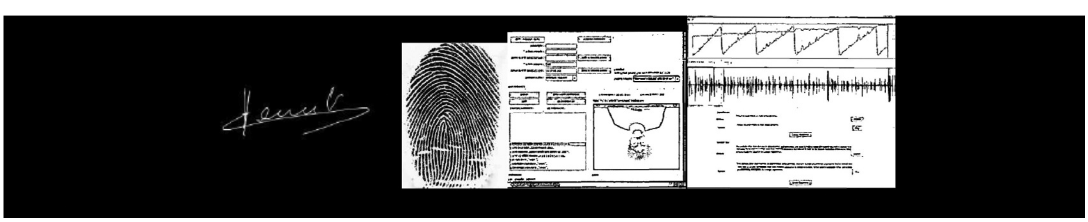

Figure 14. Sample images from MyIDea multimodal biometric database (Dumas et al., 2006).

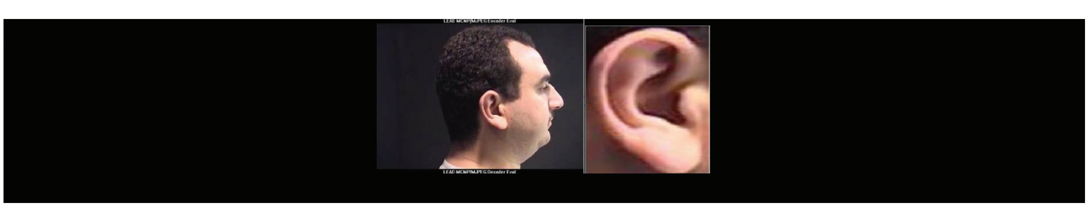

Figure 15. Sample images from UND multimodal biometric database [//cvrl.nd.edu/projects/data].

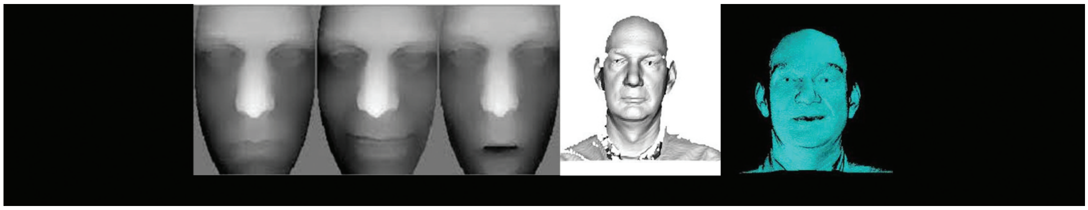

Figure 16. Sample images from FRGC multimodal biometric database [http://face.nist.gov/frgc, 2006].

Figure 17. Sample images from BIOSEC baseline multimodal biometric database (Fierrez, Ortega-garcia et al., 2007).

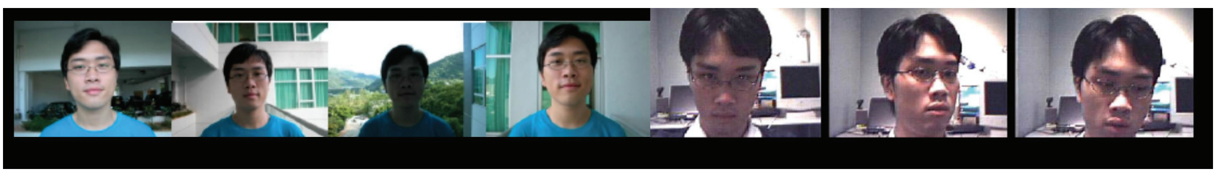

Figure 18. Sample images from M3 multimodal biometric database (H. Meng et al., 2006).

Figure 19. Sample images from BIOSEC multimodal biometric database (Toledano et al., 1995).

Figure 20. Sample images from BIOMDATA multimodal biometric database (Crihalmeanu & Ross, n.d.).

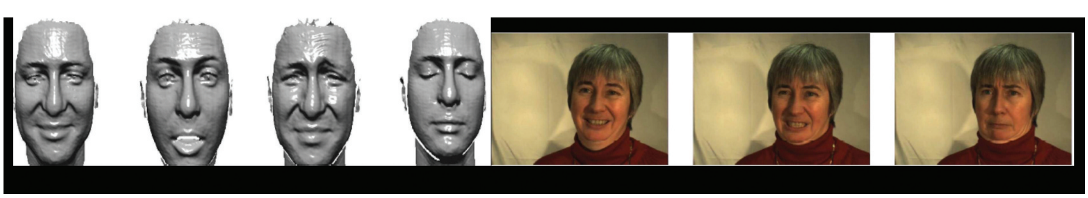

Figure 21. Sample images from IV multimodal biometric database (Lelandais et al., 2007).

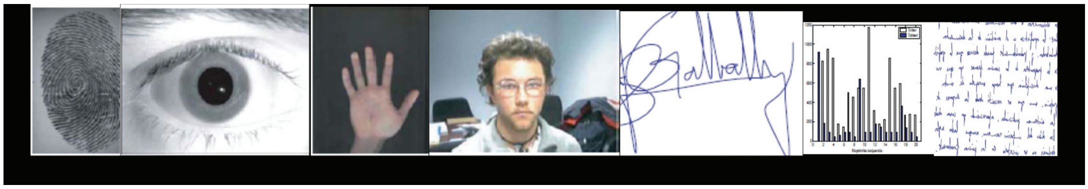

Figure 22. Sample images from BiosecurID multimodal biometric database (Fierrez, Galbally et al., 2007).

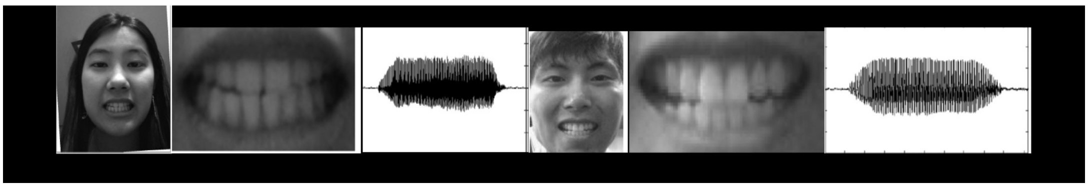

Figure 23. Sample images from FTV multimodal biometric database (Kim et al., 2010).

Figure 24. Sample images from BioSecure-DS3 multimodal biometric database (Alonso-fernandez et al., 2010).

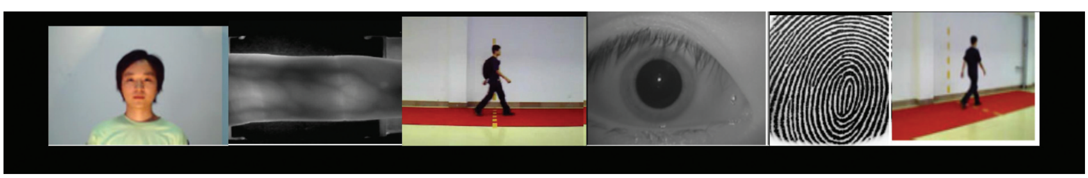

Figure 25. Sample images from SDUMLA-HMT multimodal biometric database (Yin et al., 2011).

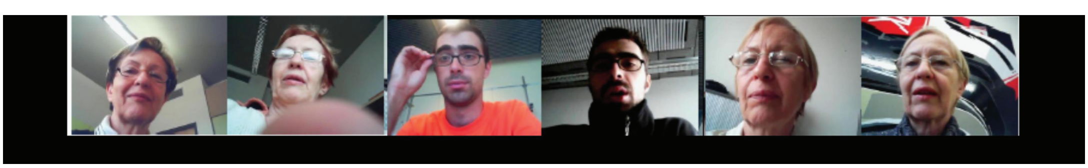

Figure 26. Sample images from MOBIO multimodal biometric database (Mccool et al., 2012).

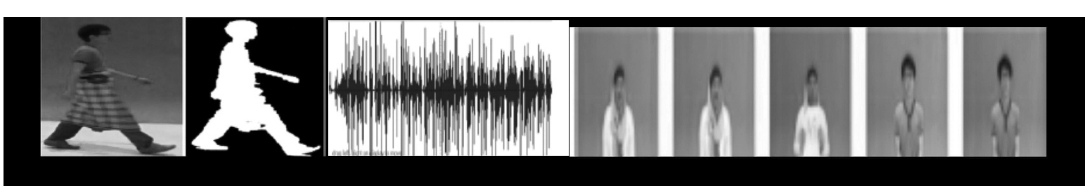

Figure 27. Sample images from MMU-GASPFA multimodal biometric database (Ho et al., 2013).

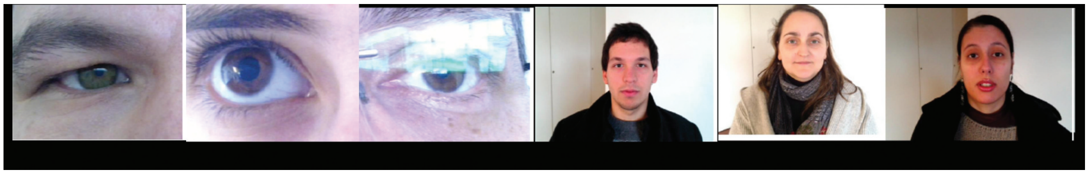

Figure 28. Sample images from MobBIO multimodal biometric database (Sequeira, 2014).

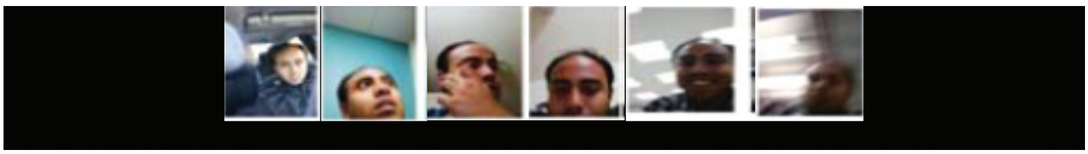

Figure 29. Sample images from UMDAA multimodal biometric database (Mahbub et al., 2016).

Figure 30. Sample images from CMBD Multimodal Biometric Database (Basak et al., 2013).

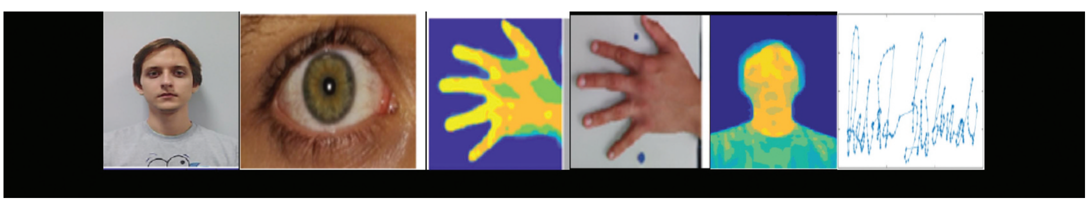

Figure 31. Sample images from MobiBits multimodal biometric database (Bartuzi et al., 2018).

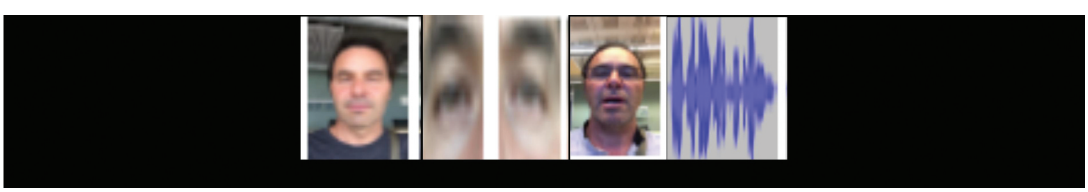

Figure 32. Sample images from MobiBits multimodal biometric database (Ramachandra et al., 2015).

Figure 33. Sample images from WVU multimodal biometric database (Crihalmeanu & Ross, n.d.).

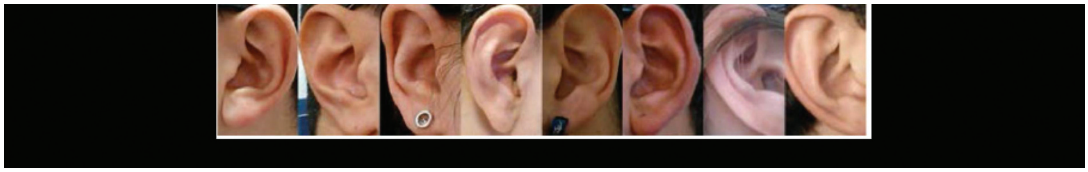

Figure 34. Sample images from I-AM multimodal biometric database (Abate et al., 2017).

a benchmark dataset of IITD with accuracy-98.19%. (Kusuma & Chua, 2011) proposed a novel multimodal face recognition framework to fuse two dimensional and three dimension facial images. They have employed fisher-faces for extracting features and validated the proposed work on two databases i.e. NTU-CSP & Bosphorus with EER of 7.1% and 6.3% respectively.

Furthermore, (Chitroub et al., 2012) proposed an efficient hand-based multimodal biometric framework to fuse fingerprint and finger-knuckle-print at image level for augmented authentication. They have used two filters i.e. minimum average correlation energy (MACE) and Unconstrained MACE (UMACE) filters to analyze the performance of the framework and approved the proposed work on PolyU FKP database and a high resolution fingerprint dataset prepared by them with EER = 0.2172%. (Chattopadhyay et al., 2015) proposed a swift and automatic multimodal biometric framework based upon gait modality. They have acquired dataset of gait videos using kinect devices for front and back views. Their results show an enhancement of 3.45% in authentication performance. (Sujatha & Chilambuchelvan, 2017) introduced discrete wavelet transform-based efficient and robust multimodal biometric framework to fuse iris, palm- print, face & signature .They have authenticated their work on CASIAv2.0 database with FRR = 2%. (P. Chen et al., 2019) presented fusion of multiple palm-prints using discrete wavelet transform-based multimodal biometric framework. They have acquired their own dataset of palm-print using a device named LPVPPIS to authenticate their work with recognition rate of 97%. (Khan, 2019) fused multiple facial images at image level to augment the authentication performance of framework. They have validated their approach on FERET database with recognition rate of 85%.

3.2. Fusion of features

(Goswami et al., 2016) introduced a classifier for biometric fusion system which works on the basis of group sparse demonstration. The GSRC algorithm employs feature level fusion and classification on the feature acquired from various traits for recognition. The proposed algorithm can encode the integral data acquired by utilizing different traits to obtain precise identification in unconstrained situations. This work is validated on WUV and LEA database with 99.1% and 62.3% accuracy respectively. Multiset Generalized Canonical Discriminant Projection (MGCDP) a novel technique for fusing traits at feature level was introduced by (Xin & Xiaojun, 2017) for the expansion of correlation of features, which belong to same class and minimization the correlation of inter class features. This method is further classified as serial MGCDP and parallel MGCDP to acquire improved recognition precision. The proposed method is validated on numerous biometric datasets with %EER in range (0.10–0.67).

Moreover, information procurement and verification strategies for biometric traits were presented by (Czyżewski et al., 2018). An investigation of the supposition of customers and of the banking tellers based on semantic strategies was performed for every single attempt for the verification of claimed identity. Decision level fusion was employed for three different cues i.e. Voice, Signature and Face for improved recognition accuracy. This work is validated on chimeric dataset. (Velmurugan & Selvarajan, 2018) exhibited an algorithm ELSA, which utilizes the hybrid fusion for the two traits of the various clients i.e. images of hand geometry and iris. In this algorithm, features of different traits are extracted by employing LBP and SIFT operators. Approach of consolidating the two distinct feature extraction techniques result in enhanced recognition accuracy in comparison with other exiting approaches. The suggested work provides recognition accuracy of 99.5% and 99.42% for ELBP and SIFT, respectively. To obtain benign digital platform for the clients of cloud, a biometric fusion framework was developed by (Sree Vidya & Chandra, 2018). Entropy-based local binary pattern ELBP has been employed for extracting features of three traits that incorporates fingerprint, face and iris, which provides improved recognition rate. Accuracy, Precision, Recall, Specificity and F-Measure have been used as evaluation metrics to validate the anticipated work.

Furthermore, (Xin et al., 2018) presented a proficient matching system which works on the basis of computation of fisher vectors. In this algorithm finger vein, face and fingerprint are fused at feature level, so the features of different traits are acquired using different feature descriptors. The presented algorithm offers improved recognition accuracy as compared to unimodal biometric systems. A feature extraction method, which works on the basis of graph for finger has been introduced by (H. H. Zhang et al., 2019). They have extracted graph features of finger images and have utilized two fusion systems i.e. sequential fusion and coding fusion system. Experimental results in terms of recognition accuracy of 99.9% show that it is an efficient multimodal biometric framework. DriverAuth – a risk-based multimodal biometric recognition framework to solve the security issues in sharing ride facilities was introduced by (S. Gupta et al., 2019).For verification of identities of registered drivers this framework integrates three cues which incorporate face, way of swipe and voice. They have assessed the suggested work on a chimeric database of 86 clients and accomplished a TAR of 96.48% and FAR of 0.02% utilizing EBT classifier.

(Gowda et al., 2019) exhibited a framework in which they have picked face, iris for feature level fusion and have assessed the framework by extracting LPQ features to enhance the recognition rate and have applied LDA for diminishing the dimensions of feature vectors, and afterward for classification KNN and SVM classifiers are used. The outcomes demonstrated 99.13% precision, which demonstrates the exceptional recognition rate of suggested framework. Multi-feature deep learning network (MDLN) architecture has been introduced by (Tiong et al., 2019).This framework utilizes traits from face and periocular regions and applied texture descriptors to enhance the recognition rate. For a unique feature depiction, MDLN utilizes feature level fusion that relates multimodal biometric information and texture descriptor. Experimental results show that proposed framework is robust with enhanced recognition rate. Another biometric fusion framework has been introduced by (Regouid et al., 2019). The suggested framework has integrated ECG signal, Ear and iris at feature level. The feature vectors of these traits are acquired by employing 1D-LBP, Shifted-1D-LBP and 1D-MRLBP. Further, to classify obscure client into genuine or impostor, KNN and RBF classifiers are utilized. The proposed framework is validated using databases of used traits i.e. CASIA, AMI and USTB1, USTB2. The test outcomes show that a CRR of 100% is accomplished with 0.5% EER.

A rectification tactic to deal with the pose variation amongst the finger trimodal images was introduced by (S. Li et al., 2019).They have also introduced a new feature extraction method which is based upon local coding for integration of three traits i.e. FP, FV and FKP. The proposed framework has applied a group of Gabor filters to augment directional features in finger images and for the complete representation of the position and orientation relationships between neighborhood pixels a generalized graph structure has been implemented. (Zhang et al., 2018) introduced a multimodal framework, which incorporates the iris and periocular traits to be integrated at the feature level to augment the recognition rate of mobile identification. To utilize complementary evidences existing in the iris and periocular they have established a deep fusion framework. To epitomize both traits in compressed form and for fusion they have applied CNN and weighted concatenation technique respectively. They have released a dataset named CASIA-Iris-Mobile-V1. 0, which is publically available and on this dataset the proposed framework achieves EER = 0.06 and FNMR = 0.0232.

(Chakraborty et al., 2016) introduced a multimodal biometric framework which utilized Side face texture and ECG as cues to be integrated at the feature level. They have utilized same techniques for extracting features of both the traits, which results in lesser computation complexity. The proposed framework was validated on chimeric dataset with Accuracy = 97%. (Jagadiswary & Saraswady, 2016) proposed a more secure fusion method, which utilizes the RSA cryptography for security of templates for three traits i.e. fingerprint, retina and finger vein. The proposed method brought improved exhibitions over the fundamental fusion model with a GAR of 95.3% and FAR of 0.01%. (Haghighat et al., 2016) introduced a multimodal framework for recognition which applied Discriminant Correlation Analysis for integrating the features of three traits i.e. frontal face, profile face and ear. Experiments performed on multiple databases with different feature descriptors for feature extraction shows that the proposed approach outperforms the other existing approaches. As the time of operation is less so this application can be utilized in real time environments.

Another feature level-based strategy for a biometric framework with face and fingerprint as cues has been exhibited by (Y. Chen et al., 2016), which has used Variational Bayesian Extreme Learning Machine (VBELM) to augment the speed of learning as this can take random input weights. Non Stationary strategy for fusing the local features of face and palmprint was introduced by (Ahmad et al., 2015). In this work, DCT block extract the local features of both the cues and provides a fused feature vector, which is applied for training of GMM-based model. This work is approved on ORL-PolyU and FERET-PolyU datasets with recognition rate of 99.7% and 97%, respectively. (Yadav et al., 2016) proposed a feature fusion-based approach to fuse the features of one modality i.e. Finger knuckle prints obtained by applying different transforms for extracting features. To utilize the proficiencies of both the transforms they have fused the features obtained using hybrid wavelet transform. A novel approach for dictionary learning using multiple cues i.e. two irises and four fingerprints has been introduced by (Bahrampour et al., 2016). They have applied stochastic gradient algorithm for learning of the framework and the results are approved on multiple datasets i.e. AR face database, the CMU Multi-PIE dataset, the IXMAS action recognition dataset and the WVU multimodal dataset.

(Veluchamy & Karlmarx, 2017) proposed fractional firefly (FFF) optimization technique to integrate the features obtained using line tracking approach from two cues i.e. finger vein and finger knuckle prints. The integration of features of both the cues is done utilizing two classifiers SVM and k-neural networks. (Aginako et al., 2017) introduced a mobile recognition approach utilizing two cues i.e. periocular and iris. Various local feature extraction methods and classifiers are applied to obtain the fused features of both the cues for better identification. (Mansouri et al., 2018) proposed a novel age identification approach on the basis of fusion of features obtained from gait using different feature extraction techniques. They have applied SM, GEI and FED descriptor to obtain features with the different characteristics to augment the system performance and validated their proposed approach on OU-ISIR database. (Toosi et al., 2017) introduced a strategy to perceive liveness of fingerprint while utilizing various feature descriptors and fusion approaches on different publically available datasets. A cancelable multimodal biometric approach was introduced by (Yang et al., 2018) for two cues i.e. fingerprint and finger-vein with adequate recognition rate.

An improved human age approximation strategy was proposed by (Punyani et al., 2018) in which they have integrated the features of two cues in two steps to achieve augments recognition. Firstly, they integrated the feature obtained from various walking time gait images and the features of various face images taken at different angles separately and in the second step they integrated the features of both cues. (Xin et al., 2018) proposed fusion of face, fingerprint and finger vein on IoMT platform. DCT-based liveness detection is utilized to identify and eliminate the fake sample images so that augmented recognition rate can be attained. To integrate feature vectors of different dimensionality fisher vector and Gaussian mixture model are utilized. Another extra secure cancelable multimodal biometric framework was proposed by (Walia, Jain et al., 2019) for face, fingerprint and iris. To reduce the dimensions of feature vector computational complexity so that this framework can be applied in real-time application, they extracted generic features of these three cues and fused at feature level.

(Saha, 2019) exhibited a profound biometric fusion framework for authentication utilizing two cues i.e. iris and retina. The goal of this work is to diminish the dimension of feature vector, so they have applied PCA-based techniques on the extracted features. The proposed work is authenticated using two benchmark datasets of IITD and DRIVE with augmented recognition accuracy. (Attallah et al., 2019) proposed another feature level fusion-based framework with two cues i.e. palm-print and finger-knuckle-print. For extracting features of these cues they have applied LBP and BSIF, respectively, and PCA to reduce the dimensionality problem. Extreme learning machine is used as classifier. The proposed framework has been validated using datasets of PolyU for both the cues. (Kumar, Chandralekha, Himaja & Sai, 2019)proposed a multimodal biometric framework, which integrated the features obtained by applying local binary patterns on two traits i.e. ear-print and finger-knuckle-print.

An approach based upon feature level fusion of lip movement and the voice signal for smartphone without need of any external hardware was proposed by (Wu et al., 2019). (Kaur, 2019) fused the features of iris and hand geometry to obtain a multimodal framework. Then chaos-based encryption techniques was used to obtain enhance security and recognition accuracy. Khatoon and Ghose (2019) fused the features of Face, Iris, and Conjunctival Vasculature using Local Ternary Patterns. Bokade (2019) fused the features obtained using PCA-based feature extraction techniques of face, palm-print and ear. Another feature fusion-based approach was proposed by Popoola and Lasisi (2020) in which feature were extracted using HOG and LBP descriptors. A multimodal framework based on swift feature extraction technique was proposed by Kumari and Thangaraj (2020). In these work features of face and fingerprint were selected using two optimization techniques i.e. Ant Colony Optimization (ACO) and the Particle Swarm Optimization (PSO).

K. Li et al. (2020) proposed an algorithm to detect exhaustion of drivers by fusing the features of driver's characteristics i.e. face, eye state and mouth state using YOLOv3 Convolution Neural Network (CNN) and SVM classifiers, so that the chances of accidents can be diminished. Meng (2020) proposed that deformation information present in the finger vein can be fused at feature level for enhanced recognition rate. Feature level fusion of multiple gait samples using CNN for personal identification was introduced by Ivanov et al. (2020). They also suggested that in near future the footwear with embedded sensors can be used as a biometric modality. (Radha et al., 2020) proposed that by fusing lip shape and lip movement at feature level, the accuracy of a visual speech recognition framework can be augmented. Purohit and Ajmera (2021) proposed a strategy for feature level fusion of fingerprint, ear and palm-print. They have applied Optimal Gray Wolf Optimization (OGWO) for selection of optimal features from extracted features to obtain reduced dimensionality and Multi-Kernel Support Vector Machine (MKSVM) algorithm for recognition.

CNN-based multimodal framework using two modalities i.e. face and periocular was proposed by (Tiong et al., 2020). They have validated their proposed work on four publically available datasets and also released a new multimodal dataset named as Ethnic-facial dataset. (Sengar, 2020) introduced feature level fusion of fingerprint and palm print, where the Gabor filters was used for extracting the features and DNN for recognition. Kaur and Sharma (2016) extracted the features of both the cues using Gabor filters and then fused these extracted features by concatenating the feature vectors to obtain multimodal biometric framework. Two touch-less cues i.e. profile face and ear-print were fused by Sarangi et al. (2018). They have applied PCA on feature vector extracted from individual cue to diminish the dimensionality and fused the features of both cues. The Kernel Discriminative Common Vector (KDCV) approach is applied on fused feature vector to obtain more distinct features. Zhang et al. (2019) proposed a multimodal framework to extract and fuse the features from iris and face using Curvelet and 2-D Gabor filter and then ELM classifier was used for recognition.

Saha (2019) proposed a PCA-based feature level fusion approach to fuse retina and iris so as to mitigate the large dimensionality issue of extracted feature vector. Ding et al. (2019) introduced a novel framework to fuse distinctive features obtained from gait by using different feature descriptors.

A cancelable multimodal biometric framework to fuse face and fingerprint at feature level utilizing EFV hashing was proposed by Lee et al. (2019). To mitigate the unsuitability between the feature sets acquired from different cues and huge dimensions (Abdulrazzaq, 2019) proposed an improved Siamese-CNN utilizing face and palm-vein. Firefly algorithm-based optimal neural network was introduced by Chanukya and Thivakaran (2019) to fuse the features extracted using Gabor filter and band pass filters from ear and fingerprint. Regouid et al. (2019) proposed innovative framework to fuse the features of three cues i.e. ECG, ear and iris, extracted using 1D-LBP, Shifted 1D-LBP and 1D-MR-LBP. KNN and RBF algorithms were employed for classification of images. Xu et al. (2019) introduced CNN-based robust framework for double layer fusion of face, iris and palmprint. Olazabal et al. (2019) proposed fusion of features of face and voice using Discriminant Correlation Analysis (DCA) and KNN classifier to augment the security of Internet of Things. They have realized their work on Rasberry-Pi-Iot device and evaluated using their own dataset.

A secure multimodal framework was suggested by Bokade (2019) utilizing three cues i.e. Face, Palm-print and ear. They have extracted features using PCA and Euclidian distance for classification. To diminish the sensor cost a CNN-based contactless framework named PCA-Net for fusing palmprint and inner finger texture acquired using only sensor was proposed by Genovese et al. (2019). Zhang et al. (2019) introduced a multimodal frame work which fused the features extracted using HOG of both the cues i.e. face and palmprint and a novel adaptive weight calculation approach for fusion of features. Soviany (2020) fused two cues i.e. fingerprint and palm-print at feature level and applied Laplace RBF kernel-based SVM for classification. Vinothkanna (2020) suggested a fuzzy vault-based multimodal framework for fusion of finger print, palm print and hand vein to obtain augmented robustness. They have generated fuzzy vault using the extracted features of three cues and chaff points obtained by employing a secret key. Joseph et al. (2020) proposed a framework with augmented security by producing a secret key to encrypt data from extracted features of three cues i.e. fingerprint, iris and palmprint utilizing MD-5 hashing algorithm.

To mitigate the curse of dimensionality in feature level fusion (Prakash et al., 2020) proposed an algorithm named fruit fly optimization (FFO) for selecting optimal features of fingerprint and iris and then applied Euclidian distance for classification. To achieve extra secure environment for storing biometric templates (Talreja et al., 2021) have united deep hashing with feature fusion approach. They have utilized face and iris as cues for their framework. (Attia et al., 2020) have applied BSIF technique to extract the features of finger dorsal surface, major knuckle-prints and minor knuckle-prints trailed by PCA so as to mitigate the large dimensionality and Cosine Mahalanobis distance for classification. A deep belief network for fusion of iris and face was suggested by Mahmoud et al. (2020). They applied R-HOG and Gabor filter for extracting features of face and iris, respectively. They authenticated suggested work on SDUMLA-HMT database with accuracy of 99%.

L. K. Singh et al. (2020) extracted features of face and fingerprint using Viola Jones and Raymond Thai Algorithm, respectively. The extracted features are fused utilizing min-max normalization approach. The suggested work is validated on chimeric dataset with average accuracy of 95.389%. Kalingani et al. (2020) introduced fusion of retina and face to obtain robust multimodal framework. They have employed PCA and Hu moments method for extracting features of face and retina respectively and then they concatenated the feature vectors obtained from both the cues. Gupta et al. (2020) proposed a novel approach in which the features extracted from both the cues i.e. iris and fingerprint were extrapolated on arbitrary plane. All the points from arbitrary plane are transformed into cylinder-shaped co-ordinates to produce different values of theta, which are then united to generate cancelable feature set.

The brief summary of papers discussed under feature level fusion section is depicted in Table 2.

Table 1. Summary of papers on sensor level fusion.

Sr No.	Authors	Biometric Traits	Database	Performance Metrics	Suggested Future Work
1	Wang et al. (2008)	Palm-print and palmvein	Own Dataset	GAR = 99.7%	Extension of dataset for analysis
2	Kisku and Tistarelli (2009)	Face & Palm-print	IITK Database	Accuracy = 98.19%	Validation of proposed work on larger database
3	Kusuma and Chua (2011)	2D-Face &3D-Face	NTU-CSP & Bosphorus 3D face databases	EER = 6.3%	Inclusion of other traits for augmented performance
4	Chitroub et al. (2012)	Fingerprint & Finger-Knuckle-Print	PolyU& Own dataset	EER = 0.2172%	Incorporation of another efficient feature descriptor on larger dataset
5	Chattopadhyay et al. (2015)	Multiple Gait	Own Dataset	Accuracy = 75.86%	Implementation of proposed work on complex real-time data
6	Sujatha and Chilambuchelvan (2017)	Iris, Palm- print, Face & Signature	CASIA v2.0	FRR = 2%	Validation of proposed work on other database
7	P. Chen et al. (2019)	Multiple Palm-Prints	PolyU	Recognition Rate = 97%	Inclusion of other traits for augmented performance
8	Khan (2019)	Multiple Facial Images	FERET	Recognition Rate = 85%	Inclusion of other traits for augmented performance

3.3. Fusion of scores

(Yildiz et al., 2016) introduced three distinct strategies for developing a database using two fingerprints, utilizing a small amount data of the integral fingerprints for expanded security of database. A fourth technique consolidates three biometric traits, for investigation of the points of confinement of biometric layering. The suggested structure is assessed utilizing publically available databases. Using FVC databases, they have obtained EER of 2.1%, 3.9% and 3.4%. Random distance method was introduced by (H. H. Kaur & Khanna, 2018), which not just produces secrecy and discriminative safeguarding revocable quasi-biometric individualities, even additionally decreases dimensionality to half. The proposed strategy is effectively examined for non-invertibilty, unlinkability and also its robustness to numerous attacks like dictionary, false accepts, and brute force. In this strategy the four traits i.e. face, palm print, palm-vein, finger-vein are integrated at score level and the proposed method is approved on CASIA-Face, CASIA-Palm-print, CASIA-Palm-Vein, CASIA-Finger-Vein datasets.

Furthermore, (Sadhya & Singh, 2017) proposed a fusion method which is based on Bayesian decision theory. In this method a novel adaptable weight assignment (DSWA) scheme and Gaussian functions has been used. They have examined the proposed method on real time database which brought about improved exhibitions over the fundamental fusion model with a GAR of 98% for a FAR of 4%.(Roy et al., 2015) introduced a multimodal framework, which incorporates the iris and face traits to be integrated at score level. FCLMS strategy is utilized for iris division and afterward GEFE calculation is applied to acquire particular highlights. This work is approved on FRGC and CASIA datasets. Results demonstrate that GEFE had a recognizable proof precision of 100%. They have recommended reconciliation of half breed hereditary element extraction and cross breed hereditary component determination to improve the presentation as future work. Another score level-based strategy for a biometric framework with multiple cues, based on s-sums has been exhibited by (Cheniti et al., 2017). The investigations were accomplished on two distinct datasets of the NIST-BSSR1 (NIST-multimodal and NIST-fingerprint). The outcomes on NIST-multimodal biometrics demonstrated that the proposed score-level fusion strategy dependent on S-via Yager, Schweizer and Sklar t-norms can perform at a high level (i.e. GAR of 99.8% at FAR = 0.01%).

A novel idea to fuse three complementary biometric cues which incorporate iris, finger vein and unique mark was introduced by (Walia, Singh et al., 2019). In this proposed idea (BSA) Backtracking Search Optimization Algorithm is applied to optimize the performance of corresponding classifiers applied for different cues. To obtain simultaneous

Table 2. Summary of papers on feature level fusion.

Sr No.	Authors	Biometric Traits	Database	Performance Metrics	Suggested Future Work
1	Zhang et al. (2015)	Iris & Periocular	CASIA-Iris-M1-S3 Dataset	EER = 0.06 and FNMR = 0.0232	Usage of non-square filters in CNN to mitigate distortion in images
2	Goswami et al. (2016)	Iris, Face & Fingerprint	WYU & LEA	WYU(Accuracy) = 62.3% LEA(Accuracy) = 99.1%	*Minimization of computational time of GSRC*
3	Chakraborty et al. (2016)	ECG & Side face	Chimeric Dataset	Accuracy = 97%	Authentication of proposed work on huge databases
4	Jagadiswary and Saraswady (2016)	Fingerprint, Retina & Finger-Vein	Chimeric Dataset	GAR = 95.3% FAR = 0.01%.	Precise selection of feature extraction and fusion techniques
5	Haghighat et al. (2016)	Frontal Face, Profile Face & Ear	WVU, BIOMDATA, AR Face Database	RR (AR) = 99.14%, RR (BIOMDATA) = 99.60, RR (WYU) = 99.85%	Application of DCA in unconfined videos
6	Y. Chen et al. (2016)	Face & Fingerprint	FERET & FVC2004	Learning Time = 0.9168 seconds	Integration of VBLEM with unsupervised learning
7	Ahmad et al. (2016)	Face & Palm-Print	ORL-PolyU, FERET-PolyU Dataset	RR(ORL-PolyU) = 99.7%, RR(FERET-PolyU)97%	Validation of this work with other levels of fusion.
8	Yadav et al. (2016)	Finger-Knuckle Prints with Different Transformations	PolyU Hong Kong FKP Database	EER = 77%	Incorporation of other trait to augment the recognition rate
9	Bahrampour et al. (2016)	Iris & Fingerprint	AR Face, CMU Multi-PIE, IXMAS and WVU Dataset	CCR(AR) = 97.14% CCR(CMU) = 81.30% CCR(IXMAS) = 94.8% CCR(WYU) = 99.10%	Use of Kinect data in multimodal action recognition
10	Kaur and Sharma (2016)	Face & Fingerprint	Chimeric Datasets	Accuracy = 99.25%	Authentication of proposed work on huge databases
11	Xin and Xiaojun (2017)	Palm-Print, Face, Fingerprint	CASIA-MS- PalmprintV1, PolyUPalmprint, CASIA-FaceV5, CASIA-FingerprintV5	EER = 0.12%	To apply MGDCP method on real data set
12	Veluchamy and Karlmarx (2017)	Finger-Vein &d Finger-Knuckle Prints	IIT Delhi Finger Knuckle & SDUMLAHMT Finger-Vein Database	Accuracy = 96%	Extension of proposed approach to obtain optimal weight score
13	Aginako et al. (2017)	Periocular & Iris	MICHE-II,VISOB	RR = 91.07%,	Multiple pattern fusion
14	Mansouri et al. (2017)	Multiple Features of Gait	OU-ISIR Database	CCR = 76.76%	Inclusion of geometric parameters
15	Toosi et al. (2017)	Fingerprints	LivDet 2011 Dataset	Optimal Average Error = 0.2%	Liveness detection of other trait
16	Czyżewski et al. (2018)	Ear and Palm-Print	Ear & Palm-Print Database of IITD	(Signature) Estimation accuracy = 60–94%. (Voice) Estimation accuracy = 60–100%, (Face) Estimation accuracy = 60–100%	Validation of this work with other levels of fusion
17	Velmurugan and Selvarajan (2018)	Hand Geometry & Iris	CASIA	Accuracy Rate = 99.5%	Improvement of proposed method using other fusion techniques.
18	Sree Vidya and Chandra (2018)	Iris, Face & Fingerprint	CASIA-Iris CASIA-Face CASIA-Fingerprint	Accuracy = 91%	Optimization of feature extraction time
19	Xin et al. (2018)	Finger-Vein, Fingerprint & Face	Chimeric Dataset	Serial Feature Fusion = 85% Parallel Feature Fusion = 83.7% FV Feature Fusion = 93.3%	Application of proposed approach on real data sets
20	Yang et al. (2018)	Fingerprint and Finger-Vein	MD-A,MD-B	EER = 0.02%	Selection of superior feature extraction technique
21	Punyani et al. (2018)	Gait & Face	OU-ISIR & USF	(OU-ISIR) Computational Time = 0.089 seconds (USF) Computational Time = 0.091 seconds	Improvement of proposed method using other fusion techniques

(*Continued*)

Table 2. (Continued).

Sr No.	Authors	Biometric Traits	Database	Performance Metrics	Suggested Future Work
22	Xin et al. (2018)	Face, Fingerprint & Finger-Vein	Chimeric Dataset	Serial feature fusion = 85% Parallel Feature Fusion = 83.7% FV Feature Fusion = 93.3%	Application of proposed approach on real data sets
23	Sarangi et al. (2018)	Profile Face & Ear-print	Chimeric Datasets	Accuracy = 99.12%	Incorporation of other levels of fusion to achieve augmented performance
24	Zhang et al. (2019)	Finger -Knuckle, Finger-Vein & Fingerprint	Chimeric Dataset	Accuracy = 99.8%, EER = 0.74%	To create a GCNN based efficient technique for tri modalities of finger.
25	Gupta et al. (2019)	Face, Swipe &Voice	Chimeric Dataset	TAR = 99.04%	To analyze driver-companion strange behavior for improvement in the proposed system.
26	Gowda et al. (2019)	Face & Iris	MEPCO	Accuracy = 99.13%	Inclusion of several classifiers to take into account behavioral cues.
27	Tiong et al. (2019)	Face & Periocular	PubFig, FaceScrub, YouTube Facial Database, RGB Public Database	Accuracy = 87.41%	Authentication of proposed work on huge databases.
28	Regouid et al. (2019)	ECG, Ear & Iris	CASIA-Iris, AMI Ear Database, ID-ECG Database	CRR = 100%, EER = 0.5%	Authentication of proposed work on huge databases.
29	S. Li et al. (2019)	Finger Vein, Fingerprint& Finger Knuckle-Prints	Chimeric Dataset	EER = 0.022% Time Cost = 0.029 Seconds	Reduction in dimensions of the feature vector
30	Walia et al. (2019)	Face, Fingerprint & Iris	SDUMLA-HMT, CASIA-FingerprintV5, FVC 2006, MCYT, CAS-PEAL, CASIA-FaceV5,, IITD PolyU, CASIA-IrisV3	DI = 5.38,EER = 1%, Recognition Index = 99.22	To achieve enhanced time complexity
31	Saha (2019)	Iris & Retina	IITD & DRIVE	Recognition Rate = 98.37%	To make the proposed system robust to noise
32	Attallah et al. (2019)	Palm-print & Finger-Knuckle-Print	Chimeric Dataset	EER = 0.49%	Authentication of proposed work on huge databases
33	P. V. Kumar et al. (2019)	Ear & Finger-Knuckle-Print	PolyU_FKP, IITD	FAR = 0.945%, FRR = 0.978, Accuracy = 98.10%	Inclusion of other feature extractor to augment the recognition rate
34	Wu et al. (2019)	Lip Movement & Voice	Chimeric Dataset	AUC = 0.9542	Investigation of proposed work for long period of time
35	Kaur (2019)	Iris & Hand Geometry	CASIA& IITD Datasets	GAR = 100%, FRR = 0%, FAR = 0.0067, Accuracy = 99%	Authentication of proposed work on huge databases
36	Khatoon and Ghose (2019)	Face, Iris & Conjunctival Vasculature	Chimeric Datasets	Accuracy = 91.14%	Improvement of proposed method using other feature extraction techniques
37	Bokade (2019)	Face, Palm-Print & Ear	Chimeric Dataset	GAR = 98.66%	Enhancement in Template Security
38	Popoola and Lasisi (2020)	Face & Fingerprint	Chimeric Dataset	For(T ≥ 90) FRR = 3.5%, FAR = 0.1%, For (90 > T > 79)FRR = 2.5%, FAR = 0.75%, For(80 > T ≥ 70) FRR = 1.65%,FAR = 1.85%	Selection of improved method for optimizing the feature vector.
39	Kumari and Thangaraj (2020)	Face & Fingerprint	FVC, Yale Face Dataset	FAR(Face) = 65.8%, FAR(Fingerprint) = 69.1%	Authentication of proposed work on huge databases
40	K. Li et al. (2020)	Face, Eye-state & Mouth-State	WIDER_FACE Database	Accuracy = 94.32%, Computation Time = 49.43 ms	Incorporation of more driver identification information.
41	Meng (2020)	Finger-Vein	HKPU & SDU-MLA Databases	EER(HKPU) = 0.0040%, EER(SDU-MLA) = 0.0266%	Inclusion of optimal feature selectors to augment the recognition rate
42	Ivanov et al. (2020)	Multiple Gait Samples	Chimeric Dataset	Accuracy = 93.3%	Inclusion of other modality for augmented recognition
43	Radha et al. (2020)	Lip shape & Lip movement	Chimeric Datasets	Recognition Rate = 94%	Authentication of proposed work on huge databases
44	L. Ching et al. (2020)	Face & Periocular	YTF, Ethnic -Facial	EER(YTF) = 16.47%, AUC(YTF) = 0.9084 EER(Ethnic -Facial) = 5.76 AUC(Ethnic -Facial) = 0.9933	Estimation of offenders using Gait analysis
45	Sengar (2020)	Fingerprint & Palm-Print	Chimeric Datasets	FRR = 0.02%, FAR = 1.3%, Accuracy = 97%	Authentication of proposed work on huge databases

(*Continued*)

Table 2. (Continued).

Sr No.	Authors	Biometric Traits	Database	Performance Metrics	Suggested Future Work
46	Zhang et al. (2019)	Iris & Face	YaleB Face Dataset and CASIA-Iris-Lamp dataset	Accuracy = 99.74%	To employ effective feature descriptor for augmented authentication
47	Saha (2019)	Retina and Iris	IITD & DRIVE	Accuracy = 98.37%	To make system less sensitive to noise
48	Ding et al. (2019)	Multiple Gait	UPCV Gait Database	CCR = 99%	Consideration of adverse situations to make the effective system
49	Lee et al. (2019).	Face & Fingerprint	FVC2004 & Face LFW Datasets	EER = 0.1%	Generalization of proposed framework for other cues
50	Abdulrazzaq (2019)	Face and Palm-Vein.	Chimeric Datasets	Accuracy = 99.33%	Authentication of proposed work on huge databases.
51	Chanukya and	Thivakaran (2019) Authentication of proposed work on huge databases.	Ear & Fingerprint	Chimeric Datasets	Accuracy = 97.33%
52	Regouid et al. (2019)	ECG, Ear & Iris	ID-ECG, USTB1, USTB2,AMI & CASIA v1 Iris Database	CRR = 100%,EER = 0.5%	Substitution of ECG signal by ECG image to achieve augmented performance
53	Xu et al. (2019)	Face, Iris & Palm-print.	CASIA, CMU PIE, PolyU	Recognition Rate = 98%	Comparison of proposed strategy with other approaches
54	Olazabal et al. (2019)	Face & Voice	Chimeric Datasets	EER = 8.04%	Inclusion of deep learning approach for augmented performance
55	Bokade (2019)	Face, Palm-print & Ear	Own Dataset	GAR = 98.66%	Enhancement of security of templates
56	Genovese et al. (2019)	Palm-print & Inner Finger Texture	Own Dataset	Accuracy = 94.46%, EER = 6.05%	To make system adaptive to unconstrained environment
57	Zhang et al. (2019)	Face & Palm-print	Chimeric Datasets	Recognition Rate = 99.74%	Authentication of proposed work on huge databases.
58	Soviany (2020)	Fingerprint & Palm-print	CASIA Datasets	True Positive Rate = 90%	Inclusion of deep learning approach for augmented performance
59	Vinothkanna (2020)	Fingerprint, Palm- Print & Hand-vein	CASIA Datasets	Accuracy = 98.5%,GAR = 0.85	Generalization of proposed framework for other cues
60	Joseph et al. (2020)	Fingerprint, Iris & Palm-Print	Own Dataset	FAR-0.15,FRR = 95.54	Authentication of proposed work on benchmark databases
61	Krishnaveni (2020)	Fingerprint & Iris	CASIA-Iris, CASIA-FingerprintV5	Accuracy = 92.23%	Analysis of other metrics to check the effectiveness of the proposed work
62	Talreja et al. (2020)	Face & Iris	WVU Multimodal Dataset	EER = 1.45%	
63	Attia et al. (2020)	Finger Dorsal Surface, Major Knuckle-Prints & Minor Knuckle-Prints	PolyU Dataset	EER = 0%	Inclusion of deep learning approach for augmented performance
64	Mahmoud et al. (2020)	Iris & Face	SDUMLA-HMT Database	Accuracy = 99%	Adoption of hybrid fusion approach for augmented authentication
65	L. K. Singh et al. (2020)	Fingerprint & Face	Chimeric Dataset	Accuracy = 95.389%	Inclusion of deep learning approach for augmented performance
66	Kalingani et al. (2020)	Retina & Face	Own Dataset	Accuracy = 99.78%	Authentication of proposed work on huge databases
67	Gupta et al. (2020)	Iris & Fingerprint	Chimeric Datasets	DI = 16.63,EER = 0.004	Inclusion of quality of image in the proposed framework
68	Purohit and Ajmera (2021)	Fingerprint, Ear, and Palm-Print	IITD Ear-Print, CASIA Palm-Print, CASIA-FingerprintV5	Sensitivity = 0.91667%, Specificity = 0.91667, Accuracy = 0.91667	Inclusion of other modality for augmented recognition

solution (PCR-6) Proportional Conflict Redistribution rules has been used. The framework shows optimal behavior irrespective of variations in environment. The suggested framework is assessed using chimeric databases. They have accomplished an EER of 1.57% and a recognition accuracy of 98.43%. (Sabri et al., 2019) suggested a serial quality multimodal biometric system. The proposed work employs numerous classifiers on the basis of quality of templates. They have proposed two recognition systems i.e. MOC and MOH. The proposed work is validated on chimeric dataset and CASIA databases. Their outcomes demonstrate that suggested method gives greater precision than the MOC and MOH using single modality by 11.29% and 5.12%, separately. A single-sensor multimodal strategy was presented by (Bhilare et al., 2018).In this proposed strategy the extracted ROIs are transformed into CS-LBP image. The left and right hand images of 185 subjects were collected to form an in-house database. The proposed strategy is validated on in-house database and openly accessible CASIA databases. Specifically, the proposed strategy accomplishes EER of 0.13 and 1.21%, respectively, for internal and CASIA databases. The consequences of the investigations performed recommend the proposed approach reliably accomplishes better execution over the current strategies considered in the study.

Moreover, (Chowdhury et al., 2018) presented an indoor-surveillance multimodal database using two traits i.e. face and voice. On this proposed database the exhibition of CNN-based face authentication and speaker identification was assessed. And the results show the advantage of fusion voice and face traits even in the worst case when both the traits were in degraded condition. Kabir et al. (2018) suggested two novel techniques for normalization and a novel weighting scheme for multimodal biometric recognition framework with score level fusion for palm print, fingerprint and ear print. Results demonstrated that the suggested framework gives least EER and most notable GAR @0.5% FAR just while any one of suggested standardization procedures or weighting system is utilized. Sultana et al. (2018) exhibited a new multimodal human recognition strategy for face, ear and social behavioral data. The social behavioral data of individuals' has been acquired from an online social network. Experimental results are validated on semi-real datasets which shows the enhanced recognition rate in comparison with conventional biometric framework.

Gianni et al. (2017) introduced a multimodal framework for recognition of students in e-learning platforms. Human administering is a non-versatile methodology, which requires an individual to screen every student remotely. In this framework traits like face, voice, touch, mouse and keystroke were utilized as traits to be fused at score level. Walia, Singh et al., (2019) introduced a framework utilizing three modalities iris, finger vein and fingerprint to be fused at score level. Fingerprint and finger vein can be acquired at the same time utilizing a solitary gadget. Backtracking Search Optimization Algorithm (BSA) is used to acquire optimized results at score level and then optimized results of matchers are combined using PCR-6 rules. The suggested framework is approved on two chimeric databases and has achieved EER = 2.28% for Database1 and EER = 1.00 for Database2. Gunasekaran et al. (2019) exhibited a profound biometric fusion framework for authentication utilizing three cues i.e. iris, fingerprint and face. The goal of this work is to diminish the dimension of feature vector in time domain; they have suggested three models to enhance the authentication rate i.e. Contour-Let Transform Model and Local Derivative Ternary Pattern Model. Furthermore, Local Derivative Ternary Pattern Model is applied to extract the distinctive features and Weighted Rank Level Fusion is applied to the extracted multimodal features and experimental results are validated on CASIA database.

Walia, Rishi et al. (2019) introduced a multimodal biometric framework for score level fusion for three cues i.e. Face, Iris and Ear. Cuckoo search optimization technique is applied to acquire optimization in the results. Then optimized results are integrated using PCR-6 rules, which is based upon DSmT. Exploratory outcomes show optimized employed score level fusion provide preferred outcomes over existing multimodal fusion techniques. Equal error rate and recognition accuracy accomplished utilizing this strategy on four chimeric databases, are 2.32 and 98.316%. Rahman (2020) introduced a multimodal recognition framework based on the integration of ECG and fingerprint at score level and the same was validated on benchmarks databases i.e. MIT-BIH, FVC2004 for ECG and fingerprint respectively. To overcome the effect of degraded ocular data on recognition performance (Proenc, 2014) fused the scores obtained using strong and weak experts on iris and eyelids respectively. The research was validated on FRGC and UBIRIS.v2 databases.

Liu et al. (2016) studied about the augmentation in recognition performance of a multimodal biometric framework using score level fusion of modalities. Ahmed et al. (2017) introduced their work in which they have fused the scores obtained by applying Multi-Block Transitional Local Binary Patterns (MB-LBP) on two cues i.e. iris and periocular. A comparative analysis and fusion of various iris and periocular classifiers was proposed by Alonso-fernandez et al. (2015) and validated their work using both NIR and visible images. Santos et al. (2014) introduced a dataset for iris and periocular which was developed using images from different mobile sets and fused these two cues to augment the recognition performance in mobile environments. Oishi et al. (2015) introduced another framework for mobile environments which fused the scores obtained using AdaBoost for two cues i.e. iris and periocular. Another multimodal framework for smartphone utilizing three cues i.e. face, periocular and iris was proposed by Martin and Christoph (2015) which was verified on different models of smartphones.

Kasban (2017) proposed a multimodal framework, utilizing fusion of voice and face at score level to augment the human recognition rate. To diminish the information loss in selecting features a bin-based matcher is introduced by Fusion et al. (2016) utilizing iris and face as cues. Srivastava et al. (2016) introduced fusion of palm-print, palm-phalanges print and dorsal hand vein to obtain augmented recognition performance at score level. They have used SVM, KNN and Random Forest for classification. To diminish the effect of spoofing attacks a robust multimodal biometric framework was proposed by Wild et al. (2015) that utilizes median filtering as a substitute of sum rule to fuse the scores of face and fingerprint. They also presented the comparative analysis of both the methods of fusion. Madane and Thepade (2016) proposed an effective multimodal framework that fused iris and palm-print scores obtained in spatial domain. They have applied Thepade's Block Truncation Coding to diminish the dimensionality of feature vectors. Kihal et al. (2017) fused 3-D cornea shape and iris at score level to augment the recognition accuracy of iris recognition framework. They have utilized Zernike polynomial expansion and Gabor filter to acquire the features of cornea shape and iris respectively.

Islam et al. (2017) introduced an extra secure algorithm to select the heart templates so that fusion of score of these templates results in enhanced recognition performance. Taheri (2018) proposed an effective approach to recognize animals by classifying their facial images. They have used different classifiers i.e. CNN and KFA to acquire the scores and then these scores were fused to augment the recognition accuracy. Naidu et al. (2018) fused face, finger and voice at score level, to enhance the recognition performance of the framework. They have employed HOG and GMM for extracting features of both cues and classification respectively. Then scores so obtained have been fused using max rule of fusion. Dwivedi and Dey (2019) introduced a double level cancelable score fusion of iris and fingerprint to obtain robust multimodal framework. Firstly, they fused the scores of both the cues using Mean-Closure Weighting (MCW) and then Rectangular Area Weighting (RAW) approach was used to obtain overall fused scores. Comparative analysis shows that the proposed approach outperforms the other exiting approaches. To add robustness to ECG-based live detection framework (Komeili et al., 2018) have fused fingerprint with ECG at score level.

Luo et al. (2019) utilized only sensor for acquisition of both the cues i.e. iris and face and one multimodal feature extraction network for extracting features to diminish the image acquirement time and the system cost. (Mansoura, 2019) extracted the features of face and iris using FFT and SVD techniques and then score obtained were normalized using percentile of data set approach to achieve optimal recognition performance. Another multimodal framework utilizing iris and face was proposed by Z. Rahman et al. (2019). They have extracted features of iris and face using PCA and Gabor filter respectively and then scores of features of both the cues have been fused using weighted sum rule method. Rahmi et al. (2019) introduced multimodal framework utilizing face and palm-print. They have extracted the features of face and palmprint using PCA and LBP, respectively. Herbadji and Guermat (2019) introduced multimodal framework utilizing iris and finger-knuckles. They have extracted features of both modalities using BSIF approach and then on the basis of grouping function they have fused the scores of both the cues.

Table 3. Summary of papers on score level fusion.

Sr No.	Authors	Biometric Traits	Database	Performance Metrics	Suggested Future Work
1	Porenca (2014)	Iris & Eyelids	FRGC & UBIRIS.v2	AUC(UBIRIS. v2) = 0.965, AUC(FRGC) = 0.973	One or more cue can also be considered to be integrated to enhance the robustness of suggested framework
2	Liu et al. (2015)	Face & Speech	BNACA Database	F-Ratio = 1.39, HTER = 3.37	Consideration of non-linear fusion techniques
3	Ahmed et al. (2015)	Iris & Periocular	MICHE II Database	EER = 1.22%	Utilization of upgraded segmentation and classification methods
4	Alonso-fernandez et al. (2015)	Iris & Periocular	BioSec, CASIA, IITD v1.0, MobBIO & UBIRIS v2	EER(BioSec) = 1.12% EER(CASIA) = 0.67% EER(IITD) = 0.59% EER(CASIA) = 0.67% 5EER (MobBIO) = 8.73% EER(UBIRIS) = 24.4%	To validate this work on VW database
5	Santos et al. (2015)	Iris & Periocular	CSIP Dataset	DI-2.331, AUC = 0.934	Inclusion of different color correction procedures to augment the performance
6	Oishi et al. (2015)	Iris & Periocular	OSIRIS,CASIA	EER = 3.6%, Identification Rate = 83.3%	To validate this work on images captured in adverse conditions
7	Raja et al. (2015)	Face, Periocular & Iris	Chimeric Dataset	EER = 0.68%	To validate this work on huge database
8	Roy et al. (2015)	Iris & Face	FRGC And CASIA	Accuracy = 100%	Integration of hybrid genetic feature selection and extraction to improve the performance.
9	Kasban (2016)	Voice & Face	Chimeric Dataset	EER = 0.64%	To validate this work on huge database
10	Milao et al. (2016)	Iris & Face	CASIA-Iris-Distance	EER = 0.35%	Up-gradation in BBC to make it user specific
11	Gopal et al. (2016)	Palm-print, Palm-Phalanges-Print & Dorsal-Hand- Vein	NSIT Palm-print Database 1.0, Bosphorus Hand Vein Database	AUC = 0.991	To validate this work on huge database
12	Wild et al. (2016)	Face & Fingerprint	(Idiap Replay-Attack Database and CASIA Face Anti-Spoofing Database, (Fingerprint Liveness Detection Competition 2013	EER = 0.47%	To augment the performance consideration of external factors affecting the fusion quality
13	Madane and Thepade (2016)	Iris & Palm-Print	IITD Database	GAR = 76.58%	To validate this work on other benchmark dataset
14	Yildiz et al. (2016)	Fingerprints	FVC NIST	EER(FVC) = 0.3% EER(NIST) = 1.2%	Exploration of further fusion techniques, for depictions of fixed-length biometric.
15	Kihal et al. (2017)	3-D Cornea Shape & Iris	Chimeric Database	EER = 0%	To validate this work on huge database
16	Islam et al. (2017)	Heart Templates	Chimeric Database	EER = 14.94%	Selection of another trait to be fused to achieve augmented recognition
17	Sadhya and Singh (2017)	Fingerprint, Face & Soft Biometric Traits	MCYT-Fingerprint-100, AR Face Database	GAR = 98%	To validate this work on large datasets.
18	Cheniti et al. (2017)	Face & Fingerprint	Multimodal dataset of NIST And Fingerprint Dataset of NIST	GAR = 99.8%	Large-scale authentication of proposed method
19	Gianni et al. (2017)	Face, Voice, Touch, Mouse and Keystroke	Chimeric Dataset	-	Testing of suggested work in real scenarios.
20	Eskandari and Sharifi (2017)	Face And Iris	CASIA-Iris Database, Chimeric Dataset	GAR = 93.62%	To validate this work on large datasets.
21	Czyżewski et al. (2018)	Voice, Signature, and Face	Own Dataset	Accuracy for MM = 94% & QM = 90%	To gather brief studies for enhancement in performance of suggested framework.
22	H. Kaur and Khanna (2018)	Face, Palm-Print, Palm-Vein, Finger-Vein	CASIA-Face, CASIA-Palm-print, CASIA-Palm-Vein, CASIA-Finger-Vein Datasets.	EER = 0.34%,DI = 8.091	To validate this work on large datasets.
23	Bhilare et al. (2018)	Finger-vein & Palm-vein	CASIA	EER = 0.13%, Identification Rate = 100%	Consideration of geometry of hands to enhance the authentication performance of the suggested framework.
24	Chowdhury et al. (2018)	Voice & Face	Chimeric Datasets	True Match Rate = 0.81	Inclusion of behavirol modality gait to improve the authentication of suggested framework.
25	Kabir et al. (2018)	Fingerprint, Palm print & Ear print	Ear Datset of AMI, Fingerprint Dataset FVC2002-DB1, COEP Palmprint Dataset, Palmprint Dataset of IITD	EER = 0.54%, GAR = 99.47%	Consideration of feature and decision level fusion with a technique based on confidence.

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Table 3. (Continued).

Sr No.	Authors	Biometric Traits	Database	Performance Metrics	Suggested Future Work
26	Sultana et al. (2018)	Face, Ear & Social Behavior Biometric	Semi-Real Data Set	Recognition Rate = 100%	Comprehensive analysis of social behavior of individuals via online social media.
27	Abozaid et al. (2018)	Voice & Face	Chimeric Dataset	EER = 0.62%	One or more cue can also be considered to be integrated to enhance the robustness of suggested framework.
28	Taheri (2018)	Multiple Facial Images	LHI-Animal-Faces dataset	Classification Rate = 95.31%	Inclusion of other traits to augment the authentication
29	Naidu et al. (2018)	Face, Finger & voice	Own Dataset	-	Expansion of the proposed dataset.
30	Dwivedi and Dey (2018)	Fingerprint & Iris	Chimeric Daraset	EER = 0.17%, GAR = 99.97%	Inclusion of other fusion level approach to augment the performance
31	Komeili et al. (2018)	Fingerprint & ECG	LivDet2015 Database	EER = 0.4%	To diminish the computational complexity
32	Luo et al. (2019)	Face & Iris	CASIA.v4-distance, FRGC v2.0	AUC = 0.9992 EER = 1.18% DI = 6.13	To validate the proposed work in non-ideal environment
33	Mansoura (2019)	Face & Iris	ORL face, Iris CASIA	RR = 98.33%	Inclusion of other fusion level approach to augment the performance
34	Z. Rahman et al. (2019)	Face & Iris	Chimeric	Accuracy = 98.9%	To validate this work on large datasets.
35	Rahmi et al. (2019)	Face & Palm-print.	ORL and PolyU Database	Accuracy = 98%	Inclusion of other traits to augment the authentication
36	Herbadji and Guermat (2019)	Iris & Finger-Knuckles	PolyU Contactless Hand Dorsal Database & IIT Delhi-1 Iris Database	CRR = 95.54%	To augment the robustness of proposed approach against fooling attacks
37	Gupta et al. (2019)	Face, Finger & Iris	Chimeric Datasets	Accuracy = 99.5%, EER = 0.5%	To make the system more adaptive
38	Aizi and Ouslim (2019)	Fingerprint & Iris	Chimeric Datasets	RR = 95%	To validate this work on real multimodal datasets
39	Haddada (2019)	Fingerprint, Face & Iris	PBMLT Database	EER = 0.1%	Inclusion of another trait i.e. DNA to augment the performance
40	Walia, Singh et al. (2019)	Fingerprint, Finger-vein & Iris	Chimeric Datasets	EER = 2.32, Accuracy = 98.316%	The proposed work can be extended for the inclusion of adaption toward different security level.
41	Sabri et al. (2019)	Fingerprints	FVC and FEI	EER = 0.007	Extension of proposed work for regulation of the accuracy.
42	Walia, Singh et al. (2019)	Iris, Finger vein & Fingerprint.	Chimeric Dataset	Accuracy = 98.43%, EER = 1.57%	Extension of suggested framework to acquire enhanced authentication accuracy.
43	Guo et al. (2019)	Face, Body & Clothing Attributes	Chimeric Dataset	EER = 0.33%, Accuracy = 98.5%	To augment the performance of system at far distance
44	Gunasekaran et al. (2019)	Face, Fingerprint & Iris	CASIA	Recognition Rate = 96%	To decipher issues like time complexity and false acceptance rate.
45	Walia et al. (2019)	Face, Iris & Ear	Chimeric Dataset	EER = 2.32%, Accuracy = 98.316%	Consideration of different traits for fusion in suggested system.
46	Su et al. (2019)	Finger Vein & ECG	ECG-ID Database And Finger Vein Database FVPolyU	EER = 1.27%, GAR = 0.9486	To implement a novel image acquirement framework for concurrently acquiring images of finger-vein and ECG signals.
47	Eskandari and Sharifi (2019)	Face & Ocular	CASIA-Iris And MBGC	Classification Rate = 93.34%	To validate this work on large datasets.
48	Lamia et al. (2019)	Multiple Fingerprints	PBMLT,FVC2002	EER = 0.22%	To make the framework more adaptive to deal with the degradation
49	P. v. Kumar et al. (2019)	Face, palm-print and signature	AR database, poly-U,MCYT-100, TIMIT Database	Accuracy = 100%	Selection of effective feature descriptor to augment the authentication
50	Z. Rahman et al. (2019)	Face & Iris	Chimeric Datasets	Accuracy = 98.9%	To validate this work on large datasets.
51	Yaman (2019)	Face and ear	UNDF, UND-J2 & FERET Datasets	Accuracy = 99.79%	To validate this work on large datasets
52	Herbadji and Guermat (2019)	Iris and finger knuckle-prints	PolyU & IIT Delhi-1 Iris Database	CRR = 95.54%	To augment the robustness of proposed approach against fooling attacks
53	Aleem et al. (2019)	Face and fingerprint	FVC 2000 DB1, FVC 2000 DB2, ORL (AT&T) & YALE Databases	Accuracy = 99.59%	To make this framework adaptive to real environment
54	Umer et al. (2019)	Periocular & Iris	MMU1, UPOL, CASIA-Iris-distance, and UBIRIS.v2	CRR = 99.76%	Selection of effective feature descriptor to augment the authentication
55	Srivastava (2020)	Face, Finger & Palm-print	IIT-D & Poly-U Data set	Accuracy = 95.48%	Extension of suggested framework to acquire enhanced authentication accuracy.
56	Zhang et al. (2020)	Face & Voice	Own Dataset	Accuracy = 98%	Inclusion of another trait to augment the performance

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Table 3. (Continued).

Sr No.	Authors	Biometric Traits	Database	Performance Metrics	Suggested Future Work
57	Rathgeb et al. (2020)	Multiple Facial Images	FERET & FRGCv2	D-EER = 8.16%	Extension of suggested framework to perform better in real scenario
58	D. K. Jain et al. (2020)	Iris & Sclera	CASIA Iris Database	True Postive Rate = 93.33%	Consideration of structural features of eyes to augment the security
59	Varshini and Aravinth (2020)	ECG, Fingerprint & Face	FVC2002/2004,Face94,Phsionet (MIT-BIH Arrhythmia)	Accuracy = 92.6%	Utilizing other fusion approach to augment the authentication
60	Ramachandran and Sankar (2020)	Iris & Palm-print	CASIA Iris Interval v4, CASIA Palm-print v1	Accuracy = 92.23%	Inclusion of another trait to augment the authentication
61	Abderrahmane et al. (2020)	Fingerprint & Face	NISTBSSR1 Multimodal, NIST-BSSR1 Fingerprint & NIST-BSSR1 Face	GAR = 91.60%, EER = 2.78%	To validate this work on large datasets.
62	Rane (2020)	Palm-print and face	Face 94, Face 95, Face 96, FERET, FRGC & IITD	GAR = 99.7%	Inclusion of another trait to augment the authentication
63	Srivastava (2020)	Retina, finger-vein and fingerprint	Chimeric Datasets	Accuracy = 91%, FAR = 89%, GAR = 95%	To validate this work on large datasets
64	Rahman (2020)	ECG & Fingerprint	MIT-BIH, FVC2004	AUC = 0.985	Large-scale authentication of proposed method

Fusion of scores of face, finger, and iris was introduced by (Gupta, Walia, & Sharma, 2019) in which the quality-dependent suppression and boosting of scores of individual cue were done to obtain computationally proficient multimodal framework. To accomplish this, they have extracted features of face and iris using Gabor filter and for fingerprint minutia-based approach has been employed. Aizi and Ouslim (2019) divided the scores of iris and fingerprint into different region of interest and then these extracted regions are fused using weighting sum and fuzzy logic-based approaches. Haddada (2019) proposed Choquet Integral-based score level fusion of fingerprint, face and the iris. To estimate fuzzy measures, they have employed Particle Swarm Optimization (PSO). Guo et al. (2019) introduced fusion of soft biometric cues i.e. face, body and clothing attributes for enhanced human recognition. They have employed SIFT and SURF descriptors to extract the features of cues and then scores of these modalities have been fused using min and max rule. Srivastava (2020) fused face, finger and palm-print, for enhanced recognition.

Zhang et al. (2020) introduced fusion of face and voice to obtain an efficient multimodal recognition framework for smartphones. For face detection and feature extraction they have employed Haar-Adaboost algorithm and Improved LBP, respectively. For extracting feature of voice they have employed MFCC-based approach. Then weighted sum rule-based approach has been used to fuse the scores of these modalities. Rathgeb et al. (2020) proposed fusion of scores obtained from altered and unaltered facial images utilizing SVM classifier. They have employed LBP, DlIb and ArcFace algorithms for extracting features. D. K. Jain et al. (2020) developed a swift and robust periocular multimodal framework utilizing iris and sclera named as PI-MED. They have employed Rubber Sheet model and MEBF model for extracting region of interest and fusing the regions, respectively. Varshini & Aravinth (2020) fused ECG, fingerprint and face to obtain robust multimodal framework at score level. As different classifiers were applied to obtain scores of these cues, so a novel approach named OVEBAMM for normalizing the sores was proposed. Ramachandran and Sankar (2020) fused iris and palm-print for enhanced recognition. They have extracted the features using three descriptors such as Log Gabor filter, LBP and HOG. For classification three distance-based matchers have been employed such as Chi-Square distance, Euclidean distance and Hamming Distance. Then the scores so obtained have been fused using weighted sum rule approach.

Abderrahmane et al. (2020) proposed a novel approach named Weighted Quasi-Arithmetic Mean (WQAM) for fusing fingerprint and face at score level. Choquet integral score level fusion of various instances of fingerprint for enhanced human recognition was proposed by Lamia et al. (2019). P. v. Kumar et al. (2019) fused behavioral and physiological cues i.e. face palm-print and signature to develop a more secure framework. Z. Rahman et al. (2019) fused the scores obtained by applying PCA approach on face

Table 4. Summary of papers on rank level fusion.

Sr No.	Authors	Biometric Traits	Database	Performance Metrics	Suggested Future Work
1	(Tharwat et al., 2012)	Ear & Finger-Knuckle-Prints	Own Dataset	Recognition Rate = 85%	Inclusion of other biometric cue and fusion technique
2	(Paul & Gavrilova, 2014)	Face & Ear	FERET, VidTIMIT, Olivet, USTB-1 & USTB-2	Recognition Rate = 100%	Implementation of proposed approach using another fusion technique
3	(Talebi et al., 2015)	Frontal face, Profile face, & Ear	FERET & USTB	Identification Rate = 96.9%	Consideration of other traits
4	(Sharma et al., 2015)	Face & Iris	NIST BSSR1, FRGCV2.0 & LG4000	Recognition Rate = 96.67%	Consideration of other one or more traits for augmented authentication
5	(W. Rahman et al., 2017)	Kinect Face & Kinect Gait	Kinect v1 Skeletal Gait Database & EUROCOM Kinect Face Dataset	Accuracy(Borda count) = 93.33% Accuracy(Logical Regression) = 96.67%	Implementation of proposed approach using other levels of fusion
6	(Gunasekaran, Raja, & Pitchai, 2019)	Face, Fingerprint & Iris	CASIA	Recognition Rate = 96%	To decipher issues like time complexity and false acceptance rate.
7	£35-(Devi, 2020)	Palmprint & Face	Chimeric Database	RR = 98.12%	To validate this work on large datasets
8	(Elhoseny et al., 2018)	Fingerprint & Iris	Fingerprint Dataset 2002 DB1, Iris Dataset CASIA V1,	FAR = 0, FRR = 0.057, Accuracy 99.86%	To validate this work on large datasets
9	(Sing et al., 2019)	Multiple Face	AT&T, UMIST, FERET & AR	Recognition Rate = 99.23%.	Inclusion of multiple classifiers for augmented authentication
10	(Jaswal & Poonia, 2020)	Palm-Print & Finger-Knuckle-Print	CASIA Palm print, IIT Delhi Palm print and PolyU FKP	CRR = 100%, EER = 0.26, DI = 3.52	Inclusion of other biometric cue and fusion technique

and Daugman approach on iris to obtain robust human recognition framework. Yaman (2019) suggested an approach to predict the age and gender by fusing profile face and ear at score level. They have employed VGG-16, ResNet-50 deep learning approaches to achieve augmented recognition. Herbadji and Guermat (2019) fused iris and finger knuckle-prints of four fingers to alleviate the shortcomings of unimodal biometric system. They employed BSIF approach to obtain the features of both the cues.

Rane (2020) fused palm-print and face at score levelbased on t-norms approach to develop robust recognition framework. Srivastava and Studies (2020) proposed a Deep Neural Network (DNN)-based approach to fuse retina, finger-vein and fingerprint to obtain robust recognition framework. To augment the robustness of cyber network (Aleem et al., 2019) fused face and fingerprint at score level. They have employed ELBP for extracting features of both the cues and to mitigate the dimensionality issues LNMF has been applied. Umer et al. (2019) proposed a Deep Neural Network (DNN)-based fusion of periocular and iris to obtain augmented recognition rate. For extracting the features and their classification they have applied Res-Net50, VGG-16 and Inception-v3 convolution neural network CNN.

3.4. Fusion of ranks

Tharwat et al. (2012) fused ear and finger-knuckle-prints at rank level to achieve augmented authentication. They have applied three feature descriptors i.e. LDA, DCT and DWT for extracting features of these two cues. PCA-based multimodal framework for fusion of face and ear at rank level was proposed by (Paul & Gavrilova, 2014). They have applied random cross folding, transformation, random projection and KNN classifier for investigating the performance. They have authenticated their work on five datasets i.e. FERET, VidTIMIT, Olivetti Research Lab Database USTB-1 and USTB-2. Hossein and Gavrilova (2015) fused frontal face, profile face, and ear at confidence-based rank level to achieve higher recognition rate. They have validated their proposed approach on FERET and USTB datasets with identification rate of 96.9%. Sharma (2015) introduced serial and parallel rank level fusion approach for face and iris. They have

Table 5. Summary of papers on decision level fusion.

Sr No.	Authors	Biometric Traits	Database	Performance Metrics	Suggested Future Work
1	(Paul et al., 2014)	Face, Ear & Signature	FERET, VidTIMIT, AT&T, USTB, RUSign	GAR = 100%	Application of other efficient fusion algorithm that can successfully enhance the authentication.
2	(Wang & Feng, 2019)	Multiple Gait	CASIA & OU-ISIR	RR = 96.2%	To validate this work on real time datasets
3	(Devi, 2020)	Palmprint & Face	Chimeric Database	RR = 98.12%	To validate this work on large datasets
4	(Iloanusi & Ejiogu, 2020)	Multiple Fingerprints	Own Dataset	Accuracy = 94.7%	To validate this work on large datasets
5	Garg, 2016)	Iris & Fingerprint	CASIA	Accuracy = 91.5%	One or more cue can also be considered to be integrated to enhance the robustness of suggested framework
6	(Naji, 2020)	Fingerprint & Face	ORL & CASIA-V5	RR = 100%	More emphasis on efficient feature descriptors to acquire the pertinent data for enhancement in performance of system.
7	(Z. Z. Ali et al., 2018)	Face & Speech Signal	Chimeric Database	Accuracy = 100%	To create the clandestine parts of cue templates to augment the robustness of the suggested framework
8	(Elhoseny et al., 2018)	Fingerprint & Iris	Fingerprint Dataset 2002 DB1, Iris Dataset CASIA V1	FAR = 0, FRR = 0.057, Accuracy 99.86%	To validate this work on large datasets
9	(P. Kumar et al., 2018)	Multiple Gait	Chimeric Dataset	Accuracy = 91.3%	Application of other efficient fusion algorithm that can successfully enhance the authentication
10	(Hezil & Boukrouche, 2017)	Voice, Signature & Face	Chimeric Dataset	RR = 100%	To gather brief studies for enhancement in performance of suggested framework

authenticated their approach on three benchmark datasets i.e. NIST BSSR1, FRGCV2.0, LG4000 with recognition rate of 96.67%.

W. Rahman et al. (2017) in this work face and gait images acquired using kinect device are fused at rank level to achieve augmented authentication. They have applied Borda count and logistic regression approaches for accomplishing fusion of kinect cues at rank level with an accuracy of 93.33% and 96.67%, respectively. Gunasekaran et al. (2019) exhibited a profound biometric fusion framework for authentication utilizing three cues i.e., iris, fingerprint and face. The goal of this work is to diminish the dimension of feature vector in time domain; they have suggested three models to enhance the authentication rate i.e., Contour Let Transform Model and Local Derivative Ternary Pattern model. Furthermore, Local Derivative Ternary Pattern model is applied to extract the distinctive features and Weighted Rank Level Fusion is applied to the extracted multimodal features and experimental results are validated on CASIA database. Devi (2020) proposed three approaches to fuse local and global feature of palm-print and face at rank level. They have extracted features using DWT and two dimensional Principal Component Analysis and fused these modalities using Maximum Rank Approach, Borda Count and Logistic Regression.

Elhoseny et al. (2018) presented a multimodal biometric framework utilizing two traits i.e. fingerprint and iris to be fused at rank level. The proposed work applied minutiae extraction for recognition of fingerprints and log-Gabor filter identification of iris. The test results shown demonstrate the improved recognition accuracy in contrast of a biometric system, which utilizes single cue in relations of FAR, FRR, and accuracy evaluation metrics. The suggested framework has achieved FAR = 0, FRR = 0.057, and Recognition rate of 99.86%.Fuzzy rank level-based approach for fusion of facial images was proposed by Sing et al. (2018).They have applied three feature descriptors and three classifiers to complete the fusion. They approved their work on four benchmark datasets i.e. AT&T, UMIST, FERET and AR with average recognition rate of 99.23%. Jaswal and Poonia (2020) suggested a multimodal biometric framework for fusion

Table 6. Summary of papers on (features and scores) level fusion.

Sr No.	Authors	Biometric Traits	Database	Performance Metrics	Suggested Future Work
1	(Kabir et al., 2019)	Fingerprint, Palm-print & Ear-print	Chimeric Dataset	GAR = 100%	To validate this work on large datasets
2	(Yaman, 2019	Ear-print & Face	UNDF, UND-J2 & FERET	Accuracy(UNDF) = 100%, Accuracy (UND-J2) = 99.79%, Accuracy(FERET) = 99.11%	One or more cue can also be considered to be integrated to enhance the robustness of suggested framework.
3	(Alay & Al-Baity, 2020)	Face, Iris & Finger-Vein	SDUMLA-HMT	Accuracy = 100%	Generalization of proposed framework so that it can perform efficiently for every trait
4	(Sireesha, 2016)	Fingerprint & Iris	CASIA	Accuracy = 85%	Analysis of proposed approach for other traits
5	(Bouzouina, 2017)	Iris & Face	CASIA-IrisV3-Interval Data base	Accuracy = 98.8%	More emphasis on efficient feature descriptors to acquire the pertinent data for enhancement in performance of system
6	(Kondapi et al., 2019)	Face, Left & Right Ocular Sections	VISOB Dataset	EER = 8%	Application of learning based technique for further Reduction in EER
7	(Su et al., 2019)	Finger Vein & ECG	ECG-ID Database, Finger Vein Database & FVPolyU	EER = 1.27%	To implement a novel image acquirement framework for concurrently acquiring images of finger-vein and ECG signals
8	(Abozaid et al., 2018)	Voice & Face	Chimeric Dataset	EER = 0.62%	One or more cue can also be considered to be integrated to enhance the robustness of suggested framework
9	(Eskandari & Sharifi, 2019)	Face & Ocular	CASIA-Iris & MBGC	Prediction rate(Female) = 93.34%, Prediction rate(Mae) = 91.67%	To validate this work on large datasets

Table 7. Summary of papers on (features, scores & decision) level fusion.

Sr No.	Authors	Biometric Traits	Database	Performance Metrics	Suggested Future Work
1	(Khellat-Kihel et al., 2016)	Finger-Vein, Fingerprint & Finger-Knuckle-Print	Chimeric Dataset	RR = 99.06%	Analysis of score level fusion of these traits
2	(Eskandari & Sharifi, 2017)	Face & Iris	CASIA-Iris Database & Chimeric Dataset	GAR = 98.87%	To validate this work on large datasets
3	(Hammad et al., 2018)	ECG & Fingerprint	Chimeric Dataset	Accuracy = 99.12%, EER = 0.10%	To validate this work on large datasets
4	(Ammour et al., 2018)	Face & Iris	CASIA Iris Distance Database	EER = 0.24%	More emphasis on efficient feature descriptors to acquire the pertinent data for enhancement in performance of system
5	(Zhou et al., 2020)	Finger-vein, Iris & Palm-vein	CASIA, PolyU & SDU	Accuracy = 99.33%	Generalization of proposed work so that it perform efficiently with other traits

of palm-print and finger-knuckle-print at rank level which is robust to spoof attacks. They have authenticated their work on CASIA Palm print, IIT Delhi Palm print and PolyU FKP databases with Accuracy = 96.22%, EER = 2.91%.

3.5. Fusion of decisions

Z. Ali et al. (2018) suggested a novel framework which encodes the biometric patterns of clients. They have fused two biometric traits i.e. face and speech signal which can be used in consolidated environment. The suggested framework applies particular handy gadgets in order to diminish the computational burden on the cloud. Experimental outcomes are validated on chimeric dataset and shows that suggested work is robust. (Elhoseny, Elkhateb, Sahlol & Hassanien, 2018) presented a multimodal biometric framework utilizing two traits i.e. fingerprint and iris to be fused at score level. The proposed work applied minutiae extraction for recognition of fingerprints and log-Gabor filter identification of iris. The test results shown demonstrate the improved recognition accuracy in contrast of a biometric system, which utilizes single

Table 8. Details of existing multimodal databases.

Database	Biometric Traits	No. of Participants	Capturing Device	Year of Release	No. of Sessions	Acquisition Environment	No. of Samples
BT-DAVID (Chibelush et al., 1996)	Lip Movement, Profile Face, Full Motion Video, Audio	124	Digital Video Camera	1999	5	Indoor	Fingerprint = 79200,Signature = 16500,Hand = 509,Voice = 7080,Face = 7080
XM2VTS (Messer et al., 2016)	Face& Voice	295	Sony VX1000E Digital Camcorder, DHR1000UX Digital VCR	1999	4	Indoor	1180
SMARTKOM (Steininger et al., 2002)	Hand, Signature, Fingerprint & Voice	96	SIVIT/Siemen, Digital Camera	2002	1	Indoor	172
BIOMET (Garcia-salicetti et al., 2003)	Face, Voice, Fingerprint, Hand and Signature	327	Conventional Digital Camera using Infrared Illumination	2003	3	Indoor	Face = 8904, Finger-Vein = 3816, Gait Videos = 6996
BANCA (Hamouz & Popovici, 2003)	Face& Voice	208	High Quality Digital Camera, Analog Camera, High-Quality and Low-Quality Microphone	2003	12	Indoor	Images = 6240,Audio-Visual Sequences = 1308
MCYT (Simon et al., 2003)	Fingerprint & Signature	330	Model 100SC – CMOS based Capacitive Capture device, Model UareU- optical capture device, WACOM Pen Tablet, Model INTUOS A6 USB	2003	1	Indoor	Fingerprint = 79200, Signature = 16500
MyIDea (Dumas et al., 2006)	Audio, Face,, Fingerprint, Hand Geometry, Palm-print, Hand Writing & Signature	104	Expensive & Cheap Camera, Optical & Sweep Sensor, Scanner, CCD Camera, Graphical Tablet & Microphone	2005	3	Indoor	Fingerprint = 180,Signature = 18,Palmprint = 24,Hand = 18
UND (https://cvrl.nd.edu/projects/data)	Face & Ear	350	Camera,3D Range Scanner	2005	2	Indoor	-
FRGC (http://face.nist.gov/frgc,2006)	2D Face & 3D Face	4003	Minolta Vivid 900/910 Series Sensor	2005	Variable	Outdoor & Indoor	-
Biosec Baseline (Fierrez, Ortega-garcia et al., 2007)	Fingerprints, Frontal Face, Iris, Voice	200	Webcam, Iris Sensor, Close-talk Headset & Distant Webcam Microphone	2006	2	Indoor	Face-1600, Voice = 11200, Iris = 3200, Fingerprint = 19200
(H. Meng et al., 2006)	Face, Fingerprint & Speech	32	Desktop PC, Pocket PC, 3 G Mobile Phone	2006	3	Indoor & Outdoor	Fingerprint = 60,Face-image = 2700 ,Face-Video = 4500 ,Audio = 4797
BIOSEC (Toledano et al., 1995)	Face, Speech & Fingerprint	250	Close-talk Headset & Distant Webcam Microphone	2007	4	Indoor	Face = 1600, Speech = 11200,Fingerprint = 19200

(*Continued*)

Table 8. (Continued).

Database	Biometric Traits	No. of Participants	Capturing Device	Year of Release	No. of Sessions	Acquisition Environment	No. of Samples
BIOMDATA (Crihalmeanu & Ross, n.d.)	Iris, Face, Face Video, Fingerprint, Hand Geometry & Palm-print	219	Irispass, CrossMatch,SecuGen,HP Scanjet, HandKey II, Sony DCR-VX2100,EVI-D30/31	2007	2	Indoor & Outdoor	6300
MBioID (Dessimoz et al., 2007)	Face, Fingerprint, Iris, Signature, Speech	120	FinePix S2 Pro (FujiFilm), A4Vision, ACCO 1394 (SHB), BM-ET 300 (Panasonic), Wacom Intuos 2 A4/Intuos 2 Inking Pen, AT3031 (Audio-Technica)	2007	2	Indoor	Face = 10, Fingerprint = 20, Iris = 10, Signature = 10, Speech = 10
IV (Lelandais et al., 2007)	Iris, 2D, 3D, Stereoscopic, &Talking Face Data	300	Digital Camera, Webcam, Stereoscopic Video Cameras, Laser Scanner, Portable Infrared Camera	2007	2	Indoor	2-D Stereoscopic Sequences = 2000 MB, 3D faces = 11 MB, 2D faces = 215 MB, Iris: 15 MB
BiosecurID (Alonso-fernandez et al., 2010)	Face, Fingerprint, Speech, Iris, Signature, Handwriting, Keystroke, Palm-print, & Hand-Geometry	400	Plantronics DSP 400, Biometrika FX2000, Yubee (Atmel sensor), LG Iris Access EOU 3000, Scanner EPSON Perfection 4990, Philips ToUcam Pro II, Wacom Intuos3 A4/ Inking pen, Labtec Standard Keyboard SE	2010	4	Indoor	Speech = 38, Finger-print = 128, Iris = 32, Hand = 32, Face = 20, Writing = 12, Signature = 28, Keystoke = 28
FTV (Kim et al., 2010)	Face, Teeth & Voice	50	HP iPAQ rw6100	2010	1	Indoor	1000
BioSecure-DS3 (Alonso-fernandez et al., 2010)	Voice, Signature, Face, Fingerprint	713	Samsung Q1, Philips SP900NC Webcam HP iPAQ hx2790 PDA	2010	2	Outdoor & Indoor	Signature = 25, Fingerprint = 12,Face = 22
SDUMLA-HMT (Yin et al., 2011)	Face, Finger vein, Gait, Iris, Fingerprint	106	Intelligent Iris Capture Device, AES2501 Swipe Fingerprint Scanner, FPR620 Optical Fingerprint Scanner, 256 × 304 FT-2BU Capacitance Fingerprint Scanner, 152 × 200 URU4000 Optical Fingerprint Scanner, 294 × 356 ZY202-B Optical Fingerprint Scanner	2011	6	Indoor	Face = 8904, Finger-Vein = 3816, Gait Videos = 6996
MOBIO (Mccool et al., 2012)	Face & Voice	153	Nokia N93i MacBook	2012	12	Indoor	105
MMU-GASPFA (Ho et al., 2013)	Gait, Speech, & Face	82	Digital Video Cameras, Digital Voice Recorder, Digital Camera, Kinect Camera & Accelerometer Equipped Smart Phones	2013	1	Indoor	Gait = 117, Speaker = 168, Face = 1019
MobBIO (Sequeira, 2014)	Voice, Face & Iris	105	Asus, Transformer Pad TF 300	2014	1	Indoor	1680
DMCS v1 (http://biometrics.dmcs.pl/en/databases/dmcsv1)	3D Face, Hand Scans	35	MBS Station Measuring Device	2015	2	Indoor	Face = 1050,Hand = 1400

(*Continued*)

Table 8. (Continued).

Database	Biometric Traits	No. of Participants	Capturing Device	Year of Release	No. of Sessions	Acquisition Environment	No. of Samples
CSIP (Q. Zhang et al., 2015)	Iris & Periocular	50	Sony Xperia Apple IPhone 4	2015	2	Indoor	2004
UMDAA (Mahbub et al., 2016)	Face & Behavirol Patterns	48	Nexus 5, front-facing camera, touchscreen, gyroscope, magnetometer, light sensor, GPS, Bluetooth, accelerometer, WiFi, proximity sensor, temperature sensor and pressure sensor.	2016	248	Indoor	49023
CMBD (Basak et al., 2013)	Iris, Fingerprint, & Face	100	Cross-Match Iris Scanner, Cross Match L-Scan Slap Fingerprint Scanner, Nikon D90 DSLR Camera	2017	2	Indoor	Fingerprint = 11350,Iris = 2660,Face = 2590
MobiBits (Bartuzi et al., 2018)	Signature, Voice, Face, Iris & Hand	53	Huawei Mate S,Huawei P9 Lite, CAT S60	2018	3	Indoor	Signature = 1940,Voice = 1220,Face = 2888,Iris = 3104,Hand = 5503
SWAN (Ramachandra et al., 2015)	Face, Periocular, Multilingual Voice	150	iPhone 6S	2019	6	Outdoor & Indoor	Face: Images = 3000 & Videos = 2700 Periocular: Images = 10500 & Videos = 4200,Audio-Visual Data = 7200
WVU (Crihalmeanu & Ross, n.d.)	Iris, Face, Voice, Fingerprint, Hand Geometry, Palm-Print	270	SONY EVI D30/31, Standard Sound Recorder Logitech, IR Recognition Systems HandKey II, HP ScanJet 4200 C, OKI IRISPASS-h handheld device	2007	2	Indoor & Outdoor	6300
MBMA (Aronowitz et al., n.d.)	Voice, Signatures & Face	100	iPhone 4s, Galaxy S2, iPad 2, Motorola Xoom	2014	184	Indoor	Voice = 736, Signatures = 1472 & Face = 552
LEA (Bharadwaj et al., 2015)	Face, Fingerprint, & Iris	18000	-	2015	-	Indoor	36000
I-AM (Abate et al., 2017)	Arm Gestures & Ear Shape	100	Samsung Galaxy S4	2017	3	Indoor	Ear = 300, Arm Gesture Video = 1200

cue in relations of FAR, FRR, and accuracy evaluation metrics. The suggested framework has achieved FAR = 0, FRR = 0.057, and Recognition rate of 99.86%.

P. Kumar et al. (2018) introduced a multimodal gait authentication strategy utilizing motion of shadow and video sequences. They have evaluated distinctive pattern of walk of people with four unique styles, to be specific ordinary walk, quick walk, walking while at the same time tuning in to song and gait when watching phone. A recognition precision of 91.3% has been achieved utilizing the GWO analyzer on styles of walking. Hezil and Boukrouche (2017) presented a multimodal system for two cue i.e. ear and palm print and have integrated these biometric traits at score level as there is no need of standardization at this degree of combination. The features of these traits are extracted using LBP, WLD and BSIF. The trial results are affirmed on ear and palm print datasets of IIT Delhi. Preliminary outcomes demonstrated a basic improvement in authentication rates as they have achieved 100% recognition rate.

Paul et al. (2014) proposed multimodal framework for analyzing social networks by fusing physical and behavirol modalities i.e. face, ear and signature at decision level. They have employed FLDA technique and KNN classifier for extracting features and classification respectively. Wang and Feng (2019) introduced a gait-based multimodal framework, in which two classifiers i.e. SVM and HMM are applied on the extracted features and then the responses of these classifiers are fused at decision level. Devi (2020) proposed three approaches to fuse local and global feature of palm-print and face at decision level. Iloanusi and Ejiogu (2020) introduced a CNN-based approach to integrate the five fingerprints at decision level to decide the gender of a person. Garg (2016) Proposed KNN-based framework for fusion of iris and fingerprint to mitigate the drawback of unimodal biometric framework. Naji (2020) extracted the features of fingerprint and face using LBP and LTP and then these cues are fused at decision level to enhance the recognition efficacy of the framework.

3.6. Fusion of features and scores

(Su, Yang, Wu, Yang, Li, Su & Lin, 2019) exhibited a multimodal biometric strategy which fuses two traits i.e. finger vein and ECG at score level fusion and utilizes Discriminant Correlation Analysis (DCA).Experimental results are validated on a chimeric database originating from finger vein database (FVPolyU) and ECG-ID dataset entitled Vein ECG originating from finger vein database (FVPolyU) and ECG-ID database provides Equal Error Rate of 1.27%. Abozaid et al. (2018) proposed a multimodal biometric framework for voice and face to be fused at feature level as well as at score level. Different feature extraction techniques were utilized to obtain features of traits. GMM classifier was utilized to simulate Cepstral Coefficients of voice biometric modality and a face differentiation method consisting of PCA and GMM classifier was utilized for face modality. The fusion results of both fusion techniques indicated that, the scores level fusion gives the least equal error rate.

Eskandari and Sharifi (2019) introduced a multimodal gender predictor framework. This framework has selected face and ocular region as biometric modalities to be fused. To extract the features of face, Uniform Local Binary Pattern (ULBP) has been applied and ocular region feature were obtained using overlapped histogram and Backtracking Search Optimization Algorithm (BSA), which gives optimized features. The proposed method is approved utilizing CASIA database of Iris and MBGC datasets. The proposed technique accomplished 92.51% enhancement in gender expectation rate for MBGC database. According to result presented a Correct Recognition Rate (CRR) of 100% has been accomplished with an Equal Error Rate (EER) of 0.5%. Double level fusion of three cues i.e. fingerprint, palm-print, and ear-print was introduced by Kabir et al. (2019) to obtain robust multimodal framework. Firstly, the features extracted from cues were fused except the one cue with least EER and then the cue with least EER and the score obtained from feature level fusion were fused.

Yaman (2019) proposed a CNN-based approach for predicting age and gender using double level fusion techniques i.e., feature level fusion and score level fusion of ear-print and face to achieve robustness in the system. (Alay & Al-Baity, 2020) proposed a CNN-based strategy to fuse multiple cues i.e. iris, face and finger-vein. They have developed two multimodal systems, one for fusing iris and face and another for fusing face, iris and finger-vein. They have applied two levels of fusion i.e. feature level and score level fusion to both the models and shows a comparative analysis of performance of models for different fusion levels. The results shows that both the models perform better for score level fusion approach. Sireesha (2016) fused fingerprint and iris at two levels i.e., score level and feature fusion and gave comparative analysis of performance of cues under different levels of fusion. They have extracted the features using LBP and Gabor filter and then for selecting optimal features GSO, PSO and AGFS have been employed.

Bouzouina (2017) proposed two approaches to fuse the iris and face i.e., at feature level and sore level. In first approach the features of face and iris are extracted using DCT and Gabor filter respectively and then these are fused and in second approach cues are fused at score level to obtain improved recognition framework. Kondapi et al. (2019) extracted features form face, left and right ocular sections by employing LBP and HOG. These features are concatenated trailed by PCA and LDA to reduce the dimension of feature vector achieved. To fuse these cues at score level Euclidian distance is used. The proposed approach is validated on benchmark Visible light mobile Ocular Biometric (VISOB) database.

3.7. Fusion of features and decisions

Hammad et al. (2018) exhibited a robust multimodal biometric framework which utilizes convolution neural network (CNN) and Q-Gaussian multi support vector machine (QG-MSVM) using feature and decision level fusion techniques. The test outcomes demonstrate that the suggested multimodal framework performs more efficiently than other prevailing multimodal validation frameworks. They have gotten EER = 0.14% for database MDB1 and EER = 0.10% for database MDB2. (Khellat-Kihel, Abrishambaf et al., 2016) proposed a double level fusion approach to mitigate the space and time complexity using kernel fisher analysis to fuse finger vein, fingerprint and the finger-knuckle-print. Zhou et al. (2020) proposed an approach in which multiple templates of finger vein are firstly fused at feature level using MDCAM technique, and then decisions of different classifiers applied on fused feature set of finger-vein, iris and palm-vein are fused to achieve final decision for authentication.

3.8. Fusion of features, scores and decisions

Eskandari and Sharifi (2017) have structured another robust multimodal biometric with amalgamation of fusion levels i.e. score level; feature level and decision level fusion simultaneously for two cues face and iris. Objective of this investigation was to construct an ideal and adaptable system with benefits of each level of fusion. They have employed ULBP and BSA for extracting and selecting features respectively. This work is approved on CASIA-Iris database and facial chimeric database. The best authentication has been accomplished as 93.91% utilizing LLR-GMM strategy of fusion. (Ammour et al., 2018) proposed the strategies of multi-modal biometric framework with feature-level fusion, score level fusion, and decision-level fusion simultaneously of texture features obtained from two iris (left eye and right eye) and one facial templates. For feature extraction, they have employed two dimensional Gabor filter integrated with SRKDA.The proposed strategies were validated on CASIA Iris Distance database. The outcomes demonstrate that the suggested multi-modal biometric framework provides appealing exhibitions of up to 0.24% EER.

After going through aforementioned research papers we are now presenting an overall statistics of the review paper. We have reviewed approximately 200 papers in this work. According to this 39% papers belong to feature level fusion, 37% papers belong to score level fusion, 6% papers are related to rank level fusion, the percentage of rank level fusion papers is also 6%, 4% papers belong to sensor level fusion and the percentage of papers related to hybrid level of fusion i.e. (feature +decision) level and (feature + score + decision) level is 1% and 2%, respectively. Hence according to this work feature level and score level fusions are the most popular levels of fusion in the literature.

4. Cancelable multimodal biometric system

Cancelable biometrics is deliberately alteration of biometric features in order to protect biometric templates. PCA-based multimodal framework for fusion of face and ear at rank level was proposed by (Paul & Gavrilova, 2014). They have applied Random cross folding, transformation, random projection and KNN classifier for investigation of performance. They have authenticated their work on five datasets i.e. FERET, VidTIMIT, Olivetti Research Lab Database USTB-1 and USTB-2. (Sree, 2016) introduced fuzzy vault-based multi-modal framework for generation of cancelable biometric template of face and fingerprint. They have also presented comparative analysis of cancelable biometric system with and without fuzzy vault. The results of proposed work shows augmented performance with GAR = 98.1%. (Dwivedi & Dey, 2019) proposed double level fusion of cancelable biometric templates of iris and fingerprint at score and decision level. They have authenticated their proposed approach on three virtual database with EER = 0.50% and GMR = 99.33%.

(Dwivedi & Dey, 2019) fused scores of cancelable biometric templates of iris and fingerprint. In order to mitigate issue of computational complexity they have utilized two weighing techniques i.e. MCW, RA. The proposed work is authenticated on two virtual datasets with EER = 0.17% and GAR = 99.97%. (Yang, Wang, Hu, Zheng & Valli, 2018) suggested the fusion of cancelable templates of fingerprint and finger-vein at feature level. They have authenticated their work on two chimeric datasets with EER = 0.12%. Random distance method was introduced by (H. H. Kaur & Khanna, 2018),which not just produces secrecy and discriminative safeguarding revocable quasi-biometric individualities, yet additionally decreases dimensionality to half. The proposed strategy is effectively examined for non-invertibilty, unlinkability and also its robustness to numerous attacks like dictionary, false accepts, and brute force. In this strategy, the four traits i.e. face, palm print, palmVein, fingerVein are integrated at score level and the proposed method is approved on CASIA-Face, CASIA-Palm-print, CASIA-Palm-Vein, CASIA-Finger-Vein datasets.

Deep learning-based cancelable multimodal biometric system was proposed by (Abdellatef et al., 2020).They have extracted the deep features of various regions of face. After fusing the feature of various regions using a fusion network they obtained fused feature set and then applied an encryption technique named bio-convolving on this fused feature set to obtain cancelable templates. They have validated their work on FERET, LFW and PaSC datasets with Accuracy = 94.02%. (Walia, Jain et al., 2019) proposed robust adaptive weighted graph-based technique for generating cancelable biometric templates. They have fused fingerprint, face, and iris at feature level. The proposed work is approved on SDUMLA-HMT, CASIA-FingerprintV5, FVC 2006, MCYT, CAS-PEAL, CASIA-FaceV5, IITD PolyU and CASIA-IrisV3 with average EER = 1.7% and RI = 97.35.

A cancelable multimodal biometric framework to fuse face and fingerprint at feature level utilizing EFV hashing was proposed by (Lee et al., 2019). (K. Gupta et al., 2020) proposed a framework to generate cancelable templates of iris and fingerprint. In this approach they have utilized particular key for each user to project the features on random plane. Transformation of projected points on random plane gives cylindrical co-ordinates. In this way, they obtained cancelable templates. For performance analysis of proposed work, they have formed a chimeric dataset by merging five benchmark database i.e. MCYT, IITD PolyU,Casia-IrisV1, FVC2006, and MMU2.On these datasets they have authenticated their work with DI = 16.63 and EER = 0.004%. (Walia et al., 2020) introduced user-specific key-based approach to generate cancelable templates of two cues i.e. iris and periocular. They have extracted deep feature of these cues by employing a network named RESNET and approved their proposed approach on two benchmark datasets i.e. IITD & MMU2 with average DI = 10.35 and EER = 0.12%.

5. Existing multimodal databases

In this work we have collected the detailed information of various existing multimodal databases for better understanding of beginners. We have also presented the sample images of databases wherever possible.

6. Vulnerability of multimodal biometric system to spoof attacks

In order to get illicit access to a secured system submission of whipped, artificially generated or unoriginal cue to sensor is known as spoof attack. (Johnson, Tan & Schuckers, 2010) suggested fusion of face, iris and fingerprint at score level, to achieve lesser vulnerability of proposed system against spoof attacks. They have validated their work on WVU database with EER = 1.76%. (Akhtar et al., 2012) introduced serial mode of fusion to fuse fingerprint and face in order to achieve lesser vulnerability against spoof attacks. They have also compared the results of serial mode fusion with parallel mode of fusion on two benchmark datasets and showed that serial mode of fusion is less vulnerable to spoof attacks. (Gomez-barrero et al., 2013) suggested fusion of scores of two cues i.e., face and iris. They estimated the strength and speed of attack in their proposed work. They have validated their work on Biosecure database with EER = 0.83%. (Gupta, Walia & Sharma, 2019) suggested fusion of iris, face and fingerprint at score level to make system more robust against spoof attacks. They have validated their work on chimeric dataset which consist of CAS-PEAL LargeScale Chinese Face Database, Casia-FaceV5, MCYT Multimodal Database, FVC2006 DB1, Casia-IrisV1, IITD PolyU and MMU2 iris database with EER = 0.87% and DI = 5.14.

(S. Kaur & Sharma, 2017) suggested an efficient technique to mitigate the issue of spoof attacks in multimodal biometric recognition. They have applied Gabor wavelets, HOG, LBP for feature extraction of face and LPQ, GLCM for fingerprint. They have fused these two cues at score level in order to achieve robustness of the system to spoof attacks. The suggested work has been validated on CASIA Face Anti-Spoofing Database and Fingerprint Liveness Detection Competition 2015 with EER = 0.35–1.05%. (Sujatha & Chilambuchelvan, 2017) proposed DAT-based robust multimodal biometric framework that fuses the palm-print, face, iris and signature. They have authenticated their work on CASIA dataset FAR = 0.003, FRR = 0.250. To check the robustness of multimodal biometric framework (Gopal & Selvakumar, 2018) introduced a software attack using two algorithms i.e. Uphill Simplex Algorithm-based hill climbing and genetic algorithm-based indirect attack. They have validated their work on Biosecure database with EER = 1.37%. They have also suggested the solution to counter affect the spoof attacks.

(Bhardwaj et al., 2016) proposed a multimodal biometric framework for physical and behavirol characteristics i.e. fingerprint and fingerprint dynamics which is resistant to fraudulent attacks. The fusion of these modalities is done at score level using sum and weighted sum rule. They have validated their work on five benchmark dataset with augmented performance i.e. AUC = 0.997, EER = 0.59%. (Jaswal & Poonia, 2020) suggested a multimodal biometric framework for fusion of palm-print and finger-knuckle-print at rank level which is robust to spoof attacks. ND-QWT and BSA have been employed for extracting and selecting the features, respectively, and authenticated their work on CASIA Palm print, IIT Delhi Palm print and PolyU FKP databases with Accuracy = 96.22%, EER = 2.91%. (S. F. Ali et al., 2021) presented a wide-ranging survey of liveness detection, spoof attacks and fingerprint matching. They have discussed about various algorithms and datasets for performance evaluation of multimodal framework and also revealed that deep learning algorithms are superior solution to these issues.

7. Challenges to multimodal biometric system

(1) Availability of effective sensors: Availability of effective sensors to acquire the images irrespective of type of illumination i.e. in indoor or outdoor environments is a requirement of a multimodal biometric framework. The sensor should be fast and efficient to capture images from a distance. So selecting or designing an effective sensor is a challenge for researchers.

(2) Availability of appropriate database: Numerous multimodal datasets are available either free or at a nominal cost. Selection of a well-designed dataset which was acquired while following the protocol standards may result in the expedite of the research work but a poor dataset may results in wastage of energy, money and time while evaluating on it. So selection of appropriate multimodal database is a challenge to researchers.

(3) Selection of efficient fusion scheme: The biometric traits can be fused by various types of levels of fusion i.e. score level fusion, feature level fusion, decision level fusion, rank level fusion etc. and also there are various fusion techniques for each level of fusion level. So while designing a particular multimodal biometric system the selection of an appropriate level of fusion and fusion schemes plays a vital role in the performance of a multimodal biometric system. So it is a challenge to decide how and when to fuse the biometric traits for designing an effective multimodal biometric system.

(4) Privacy issues: Researchers while designing a novel multimodal biometric framework try to develop the things which were not feasible in previous researches. As in biometric frameworks the personal details of individuals are stores as a database so it possible that intruders can make misuse of this data and this will result in privacy issues. So, while developing a multimodal biometric framework this is challenge to keep in mind the security of templates so that privacy issues can be mitigated.

(5) Cost-effective system: Designing of a robust, efficient and cost-effective multimodal framework for authentication is a challenge for the researcher as there is a trade-off between cost and the performance.

The aforementioned challenges could be addressed in a number of ways. We provide some concrete prospective directions for the same purpose. Regarding the sensors, development of more precise and cost-effective sensors could help. Moreover, such sensors need to be deployed which could acquire samples of multiple traits in one go. For instance, facial camera can collect samples of face, iris, and periocular biometrics in one click. Additionally, development of sensors with multi-spectral filters can prove preferable, where registered images (i.e. with pixel-to-pixel correspondence) can be acquired easily. In addition to that, collecting more realistic multimodal databases will always be nicer, as they can facilitate the genuine evaluation of multimodal systems. Further, exploration and development of efficient fusion schemes are desirable, and may be achieved through learning-based fusion schemes. These schemes are capable of learning the relationship between features and/or scores in a more representative manner, leading to superior results. Further, the privacy related concerns are solvable through applications like cancelable biometrics, where the biometric templates of the subjects can be revoked in case of potential threats, like hacking. All these solutions, if achieved in a cost-effective manner may be like cherry on top of the cake and may fit the fiscal needs of the deploying organization.

8. Future directions

(1) To furnish more realistic multimodal databases in place of chimeric databases, as the latter fail to render the correlations between various traits.

(2) To explore the possibilities of deploying deep convolutional neural networks (CNNs) in the problem of multimodal biometrics, as CNNs have proven to be amazingly efficient in solving various computer vision and image classification problems.

(3) To conduct real-life case-studies analyzing the vulnerability of multimodal systems, as it is still not known how the real-life multimodal system behaves in response to more sophisticated spoof attacks.

(4) The feasibility of using multimodal biometrics in smartphones is such an area which is not yet fully explored. Owing to the limited computational resources available on smartphones, devising computational-efficient multimodal systems would be a promising and challenging field to study.

(5) Lastly, but not the least, discovering the optimized blend of biometric traits is still a research question to be answered. More importantly, which biometric traits are there which will yield outperforming

results when fused together, and which fusion strategy would be advantageous. A large-scale realistic study is to be conducted to establish strong answers to above questions

9. Use-cases of multimodal biometrics

This section covers some practical use-cases of multimodal biometrics, which are deployed in use for long.

(1) **Aadhar Card**: The most prevalent example of real-time use-case of biometrics is Aadhar Card. It is a national identification card, which compromises of a typical twelve digits number for each person, allotted by UIDAI (Unique Identification Authority of India) (Rao & Nair, 2019)(Unique Identification Authority of India, 2012)(Barde, 2018). It is based upon biometric traits such as iris, face and fingerprint for authentication of individual. To get aadhar card an individual has to provide the biographical information such as name, gender, date of birth, address and biometric information such as fingerprint, iris and facial image. Then to check the uniqueness of this information, it is forwarded to the Central Identities Data Repository (CIDR), where de-duplication of the information is done. After these steps a 12-digit number with lifelong identification capability is allotted to a user.

(2) **Border Control**: Another imperative use-case of multimodal biometrics is border control. Border control is basically the measures taken by a state to monitor the activities on its border and the movement of people. Modern technology has also paved way to ensure border security in the most effective way through the introduction of biometrics. Biometrics are highly effective in border management as they use biologically unique traits like face and fingerprint to identify individuals trying to enter a country. E-passport plays an important role in border management (Kundra et al., 2014). E-passport is a digital passport which has a chip embedded in it. The embedded chip holds the same data as the data page of traditional passport as well as additional biometric information. As alteration of the data enclosed in this chip is a tedious task, so threat of scam or forged passport can be checked. According to International Civil Aviation Organization (ICAO) three biometric traits such as face, fingerprint and iris is deployed for authentication of user. A country which has adopted this technique for ensuring its border security is Saudi Arabia. Saudi Arabia's biometric security is based on automated fingerprint identification system (AFIS). The Saudi e-ID card is also a biometric card and is also efficient in physical and electronic identity verification (Arab, 2017). To augment the security at borders Saudi Arabia is planning to deploy iris (Daugman & Malhas, 2004) in addition to fingerprint.

(3) **Law enforcement**: Biometric continues to be an important technology to increase security in law enforcement(Coleman, 2019). Biometrics in law enforcement uses common modalities like fingerprints, face, voice & and iris. The initial use of biometrics was made by an Argentina criminologist 125 years ago. Today most countries be it United States, UK, Japan and even other developing countries have adopted biometrics for its law enforcement to ensure security for its citizens. Talking about the United States one of the most technologically advanced country, US law enforcement agency aka FBI has facial recognition records of more than 117 million Americans. Moreover, the United Kingdom's welsh police is also planning to adopt facial recognition to detect criminals and decrease crime rate but it is currently on trial basis, japan is also planning to implement facial recognition at its airports to prevent terrorists from entering in the country. Even in India in one of the operations conducted in Lahore in 2016 Punjab police employed biometrics and the modality

used there was facial recognition. Be it any country, the use of biometrics in the law agency has surged since 2017.

10. Conclusions

This paper is an attempt to disseminate the literature of research being conducted in the arena of biometric fusion for authentication. The paper starts with an argument on several bottlenecks that a unimodal biometric system may face, which primarily include scarcity of distinctive information, intra-class variations, universality and acceptability. In order to overcome these bottlenecks, the researcher fraternity has turned its attention toward amalgamation of more than one biometric trait. This fusion not only enhances the likelihood of more secure authentication system, but also mitigates the limitations of using single biometric modality. The paper describes several contemporary articles in terms of their methodologies adopted, modalities and databases employed, and results in terms of recognition accuracies and EERs. The articles are classified as per the type of fusion, because this seems to be the most intriguing classification in which the beginners/readers may find interest. This classification is also substantial as it directly relates with the corresponding accuracy achieved. In this paper, a critical analysis of approximately 200 papers has been completed to furnish more information to beginners.

In view of the detailed review presented in this paper, this can be concluded that the score-level fusion is the utmost general technique, as it does not involve any prior information about the features and classifiers. However, it is only effective when the scores from two or more modalities fall in the same range. Otherwise, the errors caused by the normalization of scores may lead to loss of information eventually resulting in poor accuracies. On the other hand, feature level fusion suffers from increased dimensionality and uncorrelated nature of the features. Whereas, sensor-level fusion cannot be regarded as an universally accepted fusion scheme as most of the times, it is very hard to fuse the modalities of interest at the sensor level. Lastly, decision level fusion, which is performed after the decision has been made by different classifiers, is very sensitive to individual classifier accuracy, which may cause erroneous decisions or biased decisions. Furthermore, it can also be concluded that majority of the literature attempts focus on combining the modalities generated from same part/region of the human body. For instance, there are several attempts to combine the performance of fingerprint, fingervein, palmprint, palmvein, and hand geometry. Similarly, a large interest has grown up for combining the metrics of iris, face, periocular and ocular images. However, interesting results may be obtained if modalities from two isolated body regions are fused together.

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