Multimodal Biometric Integration: Trends and Insights from the Past quinquennial

Diptadip Maiti[1], **Madhuchhanda Basak**[2] and **Debashis Das**[3]

[1]*Department of CSE, Techno India University, Kolkata, India*
[1]*Department of CSE, Techno India University, Kolkata, India*
[1]*Department of CSE, Techno India University, Kolkata, India*

Abstract: Recent years have seen a notable breakthrough in multimodal biometric systems, which combine numerous biometric modalities for increased security and accuracy. This paper offers a thorough analysis of recent advances in the field, addressing the many multimodal biometric strategies that have been put out by different researchers. Numerous modalities are covered by the evaluation, such as palm print, speech, iris, facial features, palm print, fingerprint, body form, gait, and more. To obtain amazing results in terms of accuracy and security, researchers have used cutting-edge methods like convolutional neural networks (CNNs), support vector machines (SVM), recurrent neural networks (RNNs), deep learning, and optimization algorithms. Many fusion strategies have been investigated to efficiently merge data from many modalities, such as feature-level fusion, decision-level fusion, and score-level fusion. Developments in template protection systems have also addressed security issues related to transmission and storage of biometric data. Even though a lot of the suggested systems have shown great accuracy rates, there are still issues with hardware restrictions, dataset biases, privacy problems, and computational costs. Prospective study avenues encompass investigating more extensive and heterogeneous datasets, crafting resilient fusion algorithms, and amalgamating cutting-edge technologies like deep learning-based biometric cryptosystems and federated learning. All things considered, the literature study demonstrates the enormous potential of multimodal biometric systems in offering safe and dependable authentication solutions for a wide range of applications, from on-line student authentication and proctoring systems to customized healthcare networks.

Keywords: Biometric modalities, Biometric template, Fusion techniques, Multimodal authentication, Multimodal dataset

1. Introduction

Physical or behavioural traits are utilized for biometric authentication or identification are known as biometric modalities. While facial recognition uses eye shape for non-intrusive, user-friendly verification, fingerprint recognition leverages the ridges and valleys on fingertips for excellent accuracy. While voice recognition uses distinctive vocal characteristics for hands-free identification, iris recognition uses stable eye patterns. The palmprint, hand shape, retina, vein pattern, gait, and keystroke dynamics are some other modalities [1]. Figure 1 shows different biometric traits of human. Because biometric features are universal and permanent, they provide uniqueness and resistance to counterfeiting, guaranteeing precise and safe identification. They are essential for reliable authentication solutions because of their acceptance and measurability as well as their interoperability with a wide range of systems [2]. Table I represent the comparison between the characteristics of different unimodal & multimodal biometric traits.
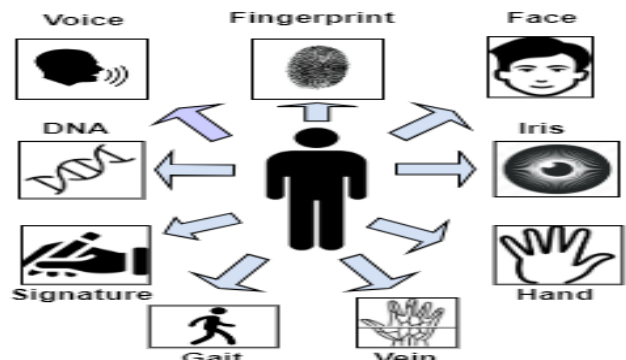

Figure 1. Biometric traits

The combination of biometric modalities is essential for improving authentication systems' accuracy and dependability [3]. In authentication systems, sensor level fusion

E-mail address: diptadipmaiti@gmail.com, madhuchhanda.basak@gmail.com, debashis.d@technoindiaeducation.com

190
quinquennial

D. Maiti, et al.: Paper Title. Multimodal Biometric Integration: Trends and Insights from the Past

TABLE I. Comparison of Different Unimodal & Multimodal BioMetric Traits.

BIOMETRIC	Mode	DISTINCTIVENESS	PERFORMANCE	COLLECTIVITY	ACCEPTABILITY	UNIVERSALITY	CIRCUMVENTION	COST	ACCURACY	REQUIRED DEVICE	USERFRIENDLINESS
FINGERPRINT	Unimodal	HIGH	HIGH	HIGH	MEDIUM	MEDIUM	LOW	MEDIUM	HIGH	SCANNER	MEDIUM
FACE	Unimodal	LOW	MEDIUM	HIGH	HIGH	HIGH	HIGH	MEDIUM	MEDIUM	CAMERA	HIGH
HAND GEOMETRY	Unimodal	MEDIUM	MEDIUM	HIGH	MEDIUM	MEDIUM	MEDIUM	LOW	MEDIUM	CAMERA	HIGH
IRIS	Unimodal	HIGH	HIGH	MEDIUM	LOW	HIGH	LOW	HIGH	HIGH	CAMERA	LOW
VOICE	Unimodal	LOW	LOW	MEDIUM	HIGH	MEDIUM	HIGH	MEDIUM	MEDIUM	MICROPHONE	HIGH
ECG	Unimodal	HIGH	HIGH	HIGH	MEDIUM	MEDIUM	LOW	MEDIUM	HIGH	ECG MACHINE	MEDIUM
FINGERPRINT & FACE	MULTIMODAL	MEDIUM	MEDIUM	HIGH	HIGH	MEDIUM	MEDIUM	MEDIUM	MEDIUM	CAMERA & SCANNER	HIGH
FINGERPRINT & IRIS	MULTIMODAL	HIGH	HIGH	LOW	HIGH	HIGH	HIGH	HIGH	HIGH	SCANNER	MEDIUM
FINGERPRINT & VOICE	MULTIMODAL	MEDIUM	LOW	HIGH	HIGH	MEDIUM	MEDIUM	LOW	LOW	SCANNER & MICROPHONE	HIGH
FACE & VOICE	MULTIMODAL	LOW	LOW	HIGH	HIGH	LOW	LOW	LOW	HIGH	CAMERA & MICROPHONE	HIGH

combines unprocessed data from several sensors that record various biometric modalities to enable thorough analysis and decision-making. Feature level fusion improves the robustness and discriminative ability of authentication systems by combining derived features from several biometric modalities into a single, unified representation [4].

Score-level fusion uses methods such as simple averaging or product rule fusion to combine matching scores from biometric matchers [5]. In order to arrive at a final choice, decision-level fusion combines the conclusions made by each classifier, using techniques like majority voting or weighted decision-making. Classifier fusion is the process of combining, either sequentially or concurrently, the outputs of classifiers trained on various modalities. To make decisions, rank-level fusion evaluates the concordance of rank orders. By using machine learning approaches, these algorithms can be customized to meet unique system needs and become even more optimized and scenario-adaptive [6].

In this research, we delve into the various advancements and cutting-edge techniques within the realm of multimodal biometrics. After the introduction in the section 1, the paper is organized as follows: Section 2 delves into the historical evolution of multimodal biometrics over the past five years. Section 3 conducts a comparative analysis and outlines future directions. Finally, in Section 4, we draw concluding remarks.

2. EVOLUTION OF MULTIMODAL BIOMETRIC

Using cutting-edge methods and decision-level fusion, Cherrat et al. [7] provide a multi-modal biometric system combining fingerprint, finger vein, and facial pictures. By using CNN, SVM classifier, Gabor filter, and linear regression line, the system outperforms single biometric systems with an accuracy of 99.43%. Larger datasets are required for algorithm robustness, and improving image quality is one of the limitations. In order to create a multi-modal biometric system that combines fingerprint and iris recognition, Mustafa et al. [5] suggest utilizing GLCM with KNN for feature extraction and an AND

gate for decision fusion. Testing on the CASIA-Iris and FVC 2004 databases, the system reaches 90% recognition accuracy; its only drawback is that preprocessing processes are not included. A hybrid biometric identification system combining fingerprint, finger vein, and facial images is proposed by Mehdi et al. [8]. It integrates CNN, Softmax, and RF classifiers. 99.49% accuracy was attained in the experiment using the SDUMLA-HMT database, with the limits of system complexity and dataset size acknowledged. A multi-modal biometric authentication system leveraging DNNs for feature extraction and MLP for minutiae recognition from fingerprint and palm print biometrics is proposed by Sengar et al. [9]. Image improvement and minute matching are part of the experimentation process, and limits regarding dataset variety and the effect of noise on accuracy are acknowledged. A multi-modal biometric authentication system incorporating speech and facial data obtained through an Android smart phone is proposed by Zhang et al. [10]. Haar cascades and Improved LBP are used for feature extraction and face detection, respectively. The system has been tested on the XJTU multi-modal database, and although there are recognized hardware constraints in smart terminal devices, it demonstrates compatibility and achieves high detection and authentication accuracy. A multi-modal biometric system that integrates ECG and fingerprint data with different fusion levels is proposed by El_Rahman et al. [11]. It achieves AUCs of up to 0.985 and 0.956 for sequential and parallel multi-modal systems, respectively, in comparison to uni-modal systems that have AUCs of up to 0.951 (ECG) and 0.866 (fingerprint). ROC curve analysis, sensitivity, specificity, and efficiency metrics are used in the study to show how effective the suggested multi-modal method is compared to current systems. Even with constraints such as a small number of modalities and the creation of a virtual multi-modal database, the performance outperforms uni-modal systems using a variety of fusion strategies and classifiers. In contrast to uni-modal systems, which have AUCs of up to 0.951 (ECG) and 0.866 (fingerprint), Byahatti et al. [4] propose a multi-modal biometric system that integrates ECG and fingerprint data

(a) Sensor label fusion

(b) Feature label fusion

(c) Score label fusion

(d) Decision label fusion
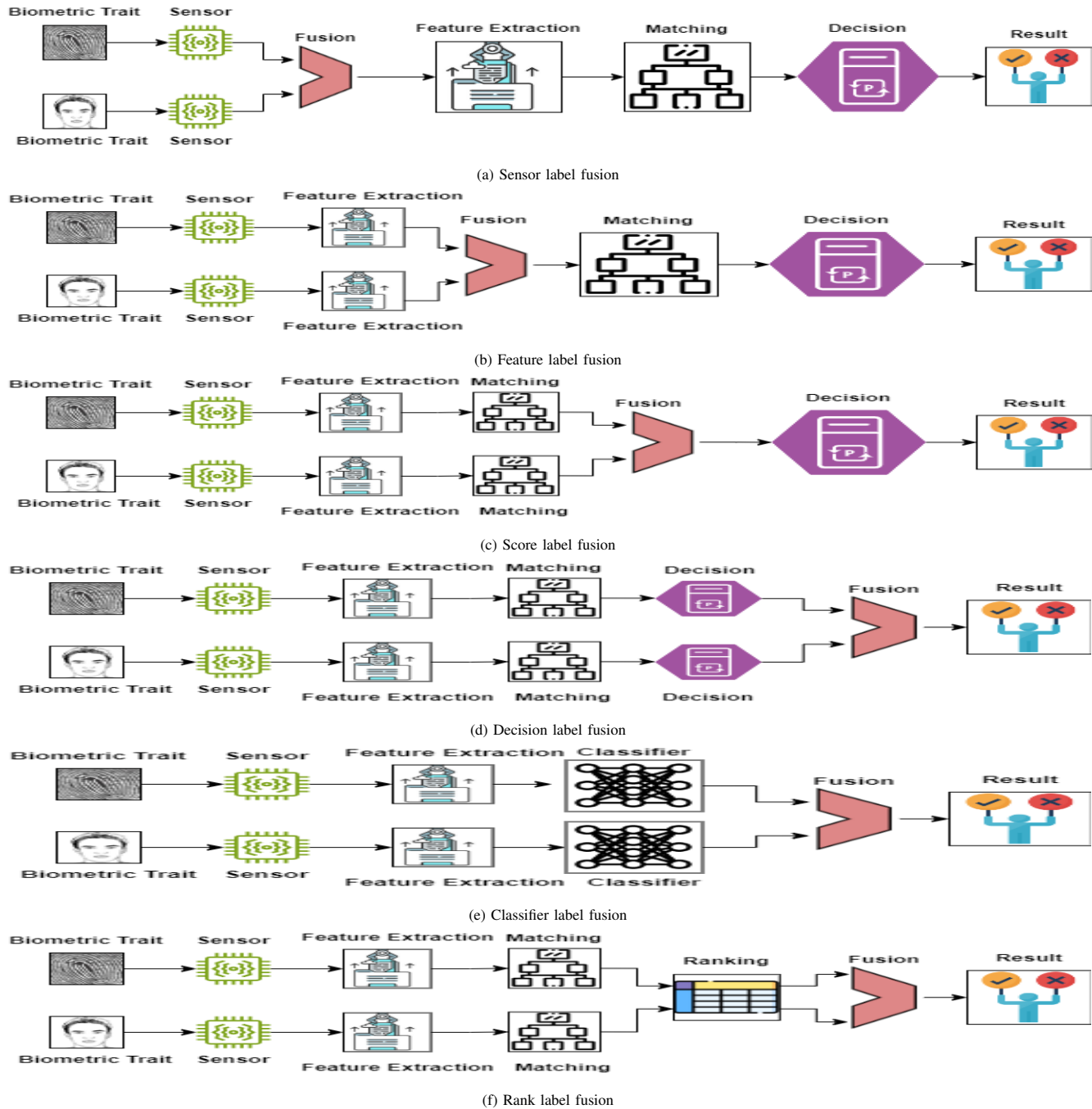
(e) Classifier label fusion

(f) Rank label fusion

Figure 2. Multimodal Biometric fusion techniques

with different fusion levels. Sequential and parallel multimodal systems achieve AUCs of up to 0.985 and 0.956, respectively. ROC curve analysis, sensitivity, specificity, and efficiency metrics are used in the study to show how effective the suggested multi-modal method is compared to current systems. Even with constraints such as a small number of modalities and the creation of a virtual multimodal database, the performance outperforms uni-modal systems using a variety of fusion strategies and classifiers. Recurrent neural networks (RNNs) based on attention are used in Zhang et al. [12] to present DeepKey, a multi-modal biometric authentication system that combines gait and EEG modalities. Beaten by baseline models and cutting-edge techniques, DeepKey attains 0% False Acceptance Rate (FAR) and 1% False Rejection Rate (FRR). The viability of the technology in the real world is nonetheless impacted

by usability constraints such as the need for two devices to be worn consecutively and intensive data collecting in lab settings. Using fingerprint, ear, and palm modalities, Purohit et al. [13] provide an ideal feature level fusion method for multi-modal biometric authentication. The methodology uses Multi-Kernel SVM for recognition and the Grasshopper Optimization Algorithm for feature selection, yielding an accuracy of 91.6%. Potential feature space incompatibility and dimensionality problems are among the limitations; however, these are lessened by the suggested optimization method. In their tokenless cancellable biometric technique, M•EFV Hashing, Lee et al. [14] utilize enhanced XOR encryption and the integration of face and fingerprint vectors into a cancellable template for multi-modal biometrics. When tested on benchmark datasets, it demonstrated somewhat worse accuracy in unimodal settings but better performance in multimodal systems. Constraints include the inability to defend against assaults using multiple compromised templates and privacy issues with feature-level fusion. In order to improve recognition performance over uni-modal systems, Kamlaskar et al. [15] propose a feature-level fusion model for iris-fingerprint multi-modal biometrics utilizing Canonical Correlation Analysis (CCA). The approach, which was tested on the SDUMLA-HMT dataset, deals with feature set redundancy, however it might have problems with segmentation and quality variations outside of the dataset. For multi-modal biometric recognition with ear, finger vein, and iris modalities, Vijay et al. [16] provide a score-level fusion technique utilizing Multi-SVNN and DBN, attaining a maximum accuracy of 95.36%. Limitations include bias in the dataset and fluctuations in illumination, distortion, and occlusion. The suggested CEWA hybrid algorithm integrates CSO and EWA. A multi-modal biometrics-based on-line student authentication and proctoring system that combines typing, speech, and facial recognition with continuous monitoring is proposed by Labayen et al. [17]. The system's accuracy of 94.25% addressed issues with noise circumstances and facial position fluctuation, but it also recognized the need for stronger biometric models. While pre- and post-exam monitoring could require some work, the system primarily monitors behaviour during exams. With early and late fusion strategies established, Leghari et al. [18] offer a feature-level fusion scheme for fingerprints and on-line signatures utilizing Convolutional Neural Networks (CNN). Using data augmentation techniques and a multi-modal biometric dataset, the system achieves increased accuracy and dependability. While admitting restricted data in related efforts and security concerns, the suggested approach demonstrates comparability with current fusion schemes. Using Random Forest classification and score-level fusion, Cherifi et al. [19] provide a robust multi-modal biometric authentication system that integrates ear and arm gesture modalities. Arm motions are assessed using the HMOG database in uncontrolled environments, and ear features are retrieved using Local Phase Quantization (LPQ) for posture and illumination robustness. Achieving an EER of 0.30% with fusion, experiments on a multi-biometric database

demonstrate the efficiency of the system despite acknowledged constraints in data quality and practical application. A unique multi-modal biometric system that combines iris and retina pictures through Levenshtein distance fusion at the comparison score level is proposed by Conti et al. [20]. The accuracy metrics obtained from the evaluation on a virtual multi-modal retina-iris database show promise, with false rejection and acceptance rates of 3.33% and 2.5%, respectively. The study draws attention to certain limitations, including the use of wholly unsupervised techniques rather than deep learning methodologies and the absence of publicly available integrated retina-iris databases. A proposed enhanced multi-modal biometric system that integrates face and iris modalities using CNN is presented by Omotosho et al. [1]. With a 98.33% recognition accuracy and an equal mistake rate of 0.0006%, the study emphasizes the necessity for larger dataset experiments and learning algorithm optimization for multi-modal systems. A multi-modal biometric system combining face and iris recognition is proposed by Xiong et al. [21], which makes use of a modified chaotic binary particle swarm optimization method. The system works better than uni-modal iris and face systems, reaching a recognition rate of up to 99.78%; nevertheless, the study's limited generalizability may result from its reliance on a single kind of iris image. A multimodal biometric system incorporating face, left, and right palm prints using CNN and KNN is proposed by Medjahed et al. [22]; accuracy rates are 99.28% for clean data and 97.14% for noisy data. Although successful, the approach does not assess the impact of image resolution and calls for more testing on larger datasets to ensure wider application. A multimodal biometric system incorporating face and finger vein modalities is proposed by Tyagi et al. [23], which achieves 100% identification accuracy on the FVR dataset by employing deep CNN-based feature extraction and score level fusion. Notwithstanding, the writers highlight certain disadvantages of multimodal systems, including higher hardware expenses and acquisition times. CNNs are used for feature extraction and five classifiers are used for authentication in El-Rahiem et al. [24]'s multimodal biometric authentication system, which combines ECG and finger vein data through deep fusion. With feature and score fusion, respectively, the system achieves low equal error rates (EERs) of 0.12% and 1.40%, indicating promise for improved security. Nonetheless, the study recognizes its limitations, including the size of the dataset and the requirement for additional research to prove robustness. A multimodal biometric identification technique employing finger vein and facial data fused at the feature layer via convolutional neural networks (CNNs) is proposed by Wang et al. [25]. On a number of datasets, the method achieves high recognition accuracy above 98.4%; yet, it is acknowledged to have drawbacks, including a small sample size and a lack of investigation into the effects of preprocessing procedures. An AI-based multimodal biometric authentication model utilizing PPG and ECG signals is proposed by Ahamed et al. [26] for individualized healthcare networks. By utilizing machine learning models such as CNN, LSTM, and Naive Bayes, the model attains

4

an EER of 0.16 and 99.8% accuracy. The requirement for a bigger and more varied dataset as well as the omission of other biometric modalities are limitations. By merging the iris and palmprint modalities using bit-transition code, Vyas et al. [3] present a feature extraction technique for multimodal biometrics. The method's findings in terms of ROC curves, EER, and AUC are encouraging when tested on benchmark databases. More comprehensive testing with larger-scale databases is required, which is the main constraint. A multimodal biometric system incorporating 3D ultrasound palmprint and hand geometry features is developed by Iula et al. [27]. Their approach uses score-level fusion on a handmade database to obtain an EER of 0.08% and a 100% identification rate. The study's limitations and limits were not specifically addressed. A template protection framework for multimodal biometric authentication is proposed by Goh et al. [28], which integrates feature-level fusion, Alignment-Free Hashing, and Index-of-Max hashing. The system provides template protection against security breaches and demonstrates state-of-the-art performance across multiple benchmark datasets. Constraints include issues with misaligned templates; deep learning-based biometric cryptosystems are recommended for future research. A multimodal biometric system using score level fusion and CNN and ORB algorithms to integrate facial and fingerprint attributes is proposed by Joseph et al. [29]. Though surpassing 96% accuracy on a dataset, the research admits dataset imbalance issues and proposes future enhancements via improved training and a variety of CNN models. Using DWT and SVD for feature extraction and logic OR for decision-making, Elisha et al. [30] suggest a two-level security system that makes use of face, fingerprint, and iris biometrics. The study highlights issues including sample storage and lighting conditions for real-time applications, while achieving 98% accuracy and 100% identification rate on datasets like ORL, AT&T, and FVC2002. To improve recognition performance in multimodal biometric systems, Ipeayeda et al. [31] presented an optimized feature fusion technique utilizing the Grey Wolf Gravitational Search Algorithm (GWGSA). Comparing the results to other fusion techniques, testing using real-world datasets showing modalities such as face, iris, and fingerprint showed better recognition accuracy and computing efficiency. Even with a high accuracy of 97.76% at threshold value 1.0, computational cost and perhaps problematic weakly correlated feature sets are drawbacks. A deep hybrid multimodal biometric recognition system incorporating five biometric traits from several sources—face, both irises, and two fingerprints—was proposed by Safavipour et al. [32]. Three methods are used by the system for feature-level fusion: quaternion-based algorithms, deep fusion in fully linked layers, and translating feature vectors into reproducing kernel Hilbert spaces (RKHS). Accuracy and efficiency of recognition were proved by experimental evaluation on six databases; nonetheless, there are several constraints such as non-universality, noise, problems with data quality, and difficulties combining different feature spaces. A multimodal biometric system integrating hand geometry and

palm print recognition from 3D ultrasound pictures of the hand was proposed by Micucci et al. [2]. Numerous fusion methods were investigated, showing enhanced identification and verification capabilities compared to unimodal systems. The paper recommends future research into alternate feature extraction and fusion strategies, notably employing machine learning and deep learning methodologies, despite restrictions such as dataset size and obtaining a 100% recognition rate. A dual multimodal biometric authentication system incorporating ECG, sclera, and fingerprint modalities was proposed by Singh et al. [33] utilizing WOA-ANN and SSA-DBN algorithms. Decision-level fusion and score-level fusion techniques were used to execute fusion on the two multimodal systems, sequential and parallel. The scalability problems in large-scale scenarios and the susceptibility to data corruption are among the constraints, despite the fact that experimental results demonstrated superior performance metrics when compared to current approaches. In order to overcome the shortcomings in image classification for biometric systems, Balogun et al. [34] developed an Optimized Negative Selection Algorithm (ONSA), which optimized the Negative Selection Algorithm (NSA) for increased efficiency and accuracy. The dataset used for the experimentation included five biometric variables that were obtained from 200 participants in an uncontrolled setting. For biometric recognition, the ONSA algorithm fared better than six other algorithms and traditional NSA, despite several drawbacks like as an artificial dataset with a small sample size. Future work is advised to improve the ONSA algorithm's performance even more. In order to extract features from images of the iris, palm print, and lips, Vasavi et al. [35] presented a new Multimodal Biometric Feature Extraction (MBFE) model that makes use of a modified Ranking-based Deep Convolution Neural Network (RDCNN). Their model achieves higher accuracy, precision, recall, and F1 score than current deep learning techniques. Using a dataset comprising iris, palm print, and lip images, the study acknowledged the difficulties associated with multimodal biometric fusion while claiming higher performance when compared to conventional techniques including BPNN, HIUWT, SMNR, and DILA. A multimodal biometric authentication system integrating speech and face recognition utilizing FaceNet for face recognition and GMM for voice recognition, with score-level fusion, was presented by Alharbi et al. [36]. The experimental data yielded an EER of 1.62%, exceeding previous techniques, by combining the VCTK and VoxCeleb datasets. Due to limitations in dataset size and diversity, larger and more diverse datasets should be used for future analysis. A Cancelable Biometric System (CBS) merging EEG signals and biometric photographs through optical encryption and watermarking was proposed by Salama et al. [37]. To ensure cancelation, EEG signals and face images are combined and encrypted using DRPE, OSH, or their cascade combinations. AROC close to 1 and EER near to 0, obtained from evaluation on several datasets, indicate good dependability. Restrictions include user collaboration, dataset size limitations, and dependence on signal quality. A multimodal biometric identification

system using Federated Learning (FL) and convolutional neural networks (CNN) using photoplethysmography (PPG) and electrocardiogram (ECG) signals was proposed by Coelho et al. [38]. TROIKA, BIDMC, and CapnoBase datasets were used. Strong security was ensured by the FL method with two sequential CNNs, which produced excellent accuracy and low false acceptance rates. Limited availability of health data, variability of data, and processing demands for FL model training are some of the constraints. A multimodal biometric system combining face, fingerprint, and signature modalities with feature extraction methods like Principal Component Analysis and Stationary Wavelet Transform is proposed by Kazi et al. [39]. They assess system accuracy on the YALE-FVC2002KVKR database by utilizing score and decision level fusion, tackling issues such as spoof attacks and noisy data. The goal of the project is to increase the dependability of biometric systems by using multimodal techniques to overcome constraints. Using both conventional techniques and deep learning, El_Rahman et al. [40] suggest improved unimodal and multimodal biometric recognition systems utilizing fingerprints and ECG signals. Multimodal systems outperform unimodal ones when evaluated on virtual datasets such as the MIT-BIH ECG and FVC2004 fingerprint databases. The lack of ECG databases, the difficulty in locating real-world datasets, and the high processing costs associated with deep learning models are some of the limitations. A deep learning-based multi-modal biometric fusion model that integrates score, feature, and pixel layers to improve recognition accuracy is proposed by Byeon et al. [41]. Using Euclidean distance metric learning and modality-specific network training for practicality, evaluation on a simulated dataset containing iris, fingerprint, and face data demonstrates 99.6% accuracy. The accuracy rates may be impacted by limitations resulting from the reliability of the dataset. An HGSSA-bi LSTM model combining iris and fingerprint biometrics is proposed by Priyani et al. [42], with accuracy of 98.5%. The model shows great sensitivity and precision when tested on the CASIA dataset, but it also recognizes the expense and complexity of multimodal systems. "Secure Sense," a multimodal biometric system that combines face, fingerprint, and iris data and achieves 93% accuracy, is proposed by Samatha et al. [43]. Decision-level fusion technique improves strong authentication by leveraging real-time and web-based datasets, which overcomes the drawbacks of unimodal systems. Using iPhone 14 Pro Max images for face, hand, and iris recognition, Kadhim et al. [44] present MULBv1, a multimodal biometric database for face recognition. With an accuracy rate of 97.41%, Deep CNN draws attention to the logistical, ethical, and technical difficulties involved in creating true multimodal datasets. GC-MMBR, a unique multimodal biometric recognition method based on MGC and Minkowski distance, is introduced by Gunasekaran et al. [45]. The technique performs well on the CASIA Biometric Ideal Test Dataset, however it is limited by the small sample size and incompleteness of the dataset. A multimodal biometric identification system incorporating VGG19-SC for iris and

facial biometrics is introduced by Amin et al. [46], with a 99.39% accuracy rate. Using a dataset of 190 individuals, the strategy applies feature-level and score-level fusion techniques; nonetheless, scalability and implementation costs are recognized as limits. A finger vein-based multimodal biometric system with 99.83% accuracy is proposed by Subramaniam et al. [6]. It does this by merging data from many fingers using CNN and correlation-based matching. The method performs better than current methods, however accuracy is impacted by issues like intra-class variance and noisy data. An FRMSDNET classifier for multimodal biometric authentication is introduced by Parvathy et al. [47], utilizing preprocessing methods such as KSCM and AOMS in conjunction with iris and fingerprint information. The system outperforms existing approaches with a high accuracy of 99.29%; nevertheless, it also recognizes that there are still obstacles and that multimodal recognition requires more security measures. FarSight, an advanced biometric recognition system that combines face, gait, and body form features to address image quality and domain gap issues, is presented by Liu et al. [48]. Using multimodal fusion techniques, the system outperforms existing methods on the BRIAR dataset, achieving considerable performance increases. FarSight exhibits potential for reliable biometric detection in a variety of settings, despite its reliance on deep learning and limits in 3D body shape integration.

3. Comparative Analysis and Future Directives

The experiments listed in the Table II use a wide range of methodology, from straightforward fusion procedures to intricate deep learning strategies. Some scholars concentrate on conventional fusion techniques, while others investigate the potential of convolutional neural networks (CNNs) and other cutting-edge algorithms. The investigations differ in their level of sophistication; some use sophisticated algorithms that go through several phases of feature extraction and fusion. The investigations take into account a wide range of biometric modalities, such as face, fingerprint, iris, ECG, gait, palm print, finger vein, hand geometry, voice, retina, hand shape, and EEG. Some research focus on a single modality, while others look at the advantages of mixing many senses to increase the robustness and performance of the system. The datasets utilized in the research are derived from a variety of sources, including synthetic datasets, self-collected datasets, and publicly accessible benchmark datasets. The dataset sizes differ greatly amongst the research; some use bigger databases like FVC and CASIA, while others depend on smaller or self-collected datasets. Metrics for evaluating performance include accuracy, precision, recall, F1-score, rank-1 recognition rates, equal error rate (EER), false acceptance rate (FAR), false rejection rate (FRR), receiver operating characteristic (ROC) curves, and verification or identification rates. Various assessment procedures, including combination techniques, decision-level fusion, score-level fusion, and feature-level fusion, are used in different investigations. Numerous tests show high accuracy rates that surpass 90% and, in certain situations, even 100%.

However, each study's methodology, modalities, datasets, and performance indicators have an impact on how accurate the results are. Figure 3 shows the distribution of accuracy across different studied methods. It shows that majority of the methods accuracy lies between 96-99%.
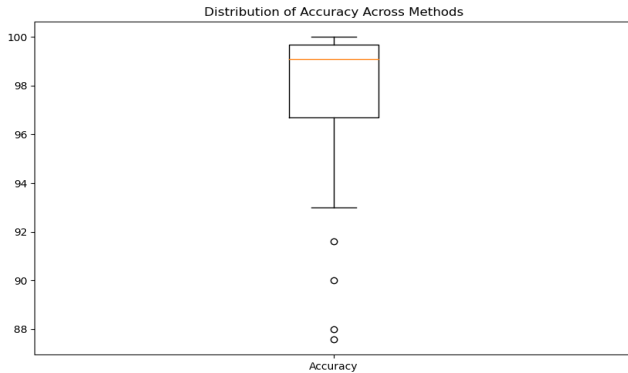

Figure 3. Distribution of accuracy across methods

Figure 4 represents the frequency distribution of accuracy between the studied methods. Out of the study majority methods have achieved higher accuracy and can be tested for practical implementation.
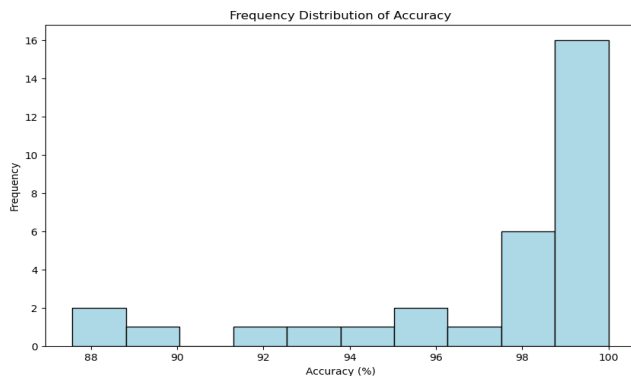

Figure 4. Frequency distribution of accuracy

Numerous studies have shown some common drawbacks, such as noisy data, spoof attacks, restricted availability of datasets, problems with scalability, computational complexity, high implementation costs, reliance on particular thresholds, and privacy and security concerns. Additionally highlighted are dataset-specific issues such picture distortion, occlusion, noise in images, illumination changes, dataset bias, and dataset inconsistencies. Figure 5 shows the pie chart of the limitation of the studied methods. Almost 47% methods suffers from limited dataset which eventually ask the generalization of the methods for practical implementation. Only combination of few modalities have been studied by almost 31% methods. Around 19% methods suffers from complex implementation techniques that makes

them unsuitable to implement them in low memory and low power consuming biometric systems. Lack of handling different attack are faced by almost 5% of the studied methods. Even with high accuracy rates, a number of studies point out areas that could still be improved, including handling data distortion and noise, strengthening security and privacy precautions, expanding the quantity and variety of datasets, investigating liveness detecting techniques, and simplifying computational complexity. Interoperability with cutting-edge technologies like edge computing, block chain, and AI-powered encryption methods could improve multimodal biometric systems' resilience and security even more.
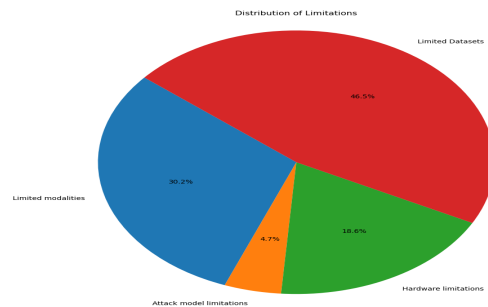

Figure 5. Distribution of limitations

4. CONCLUSION

Numerous approaches, modalities, datasets, and performance indicators are revealed by comparing the studies on multimodal biometric systems. Even though a number of methods show promising accuracy rates of above 90%, the area still has to deal with issues including computational complexity, noisy data, privacy problems, and limited dataset availability. In order to overcome these issues, future research efforts should concentrate on boosting data quality, strengthening security and privacy protocols, diversifying datasets, and investigating cutting-edge technology. Multimodal biometric systems can be made even more accurate and resilient by overcoming these drawbacks, which will open the door for their broad use in a variety of applications such as identity verification, security, and authentication.

REFERENCES

[1] L. Omotosho, I. Ogundoyin, O. Adebayo, and J. Oyeniyi, "An enhanced multimodal biometric system based on convolutional neural network," *Journal of Engineering Studies and Research*, vol. 27, no. 2, pp. 73–81, 2021.

[2] M. Micucci and A. Iula, "Recognition performance analysis of a multimodal biometric system based on the fusion of 3d ultrasound hand-geometry and palmprint," *Sensors*, vol. 23, no. 7, p. 3653, 2023.

[3] R. Vyas, T. Kanumuri, G. Sheoran, and P. Dubey, "Accurate feature extraction for multimodal biometrics combining iris and palmprint," *Journal of Ambient Intelligence and Humanized Computing*, vol. 13, no. 12, pp. 5581–5589, 2022.

7

196
quinquennial

D. Maiti, et al.: Paper Title. Multimodal Biometric Integration: Trends and Insights from the Past

TABLE II. Comparative Analysis of Multi-Modal Biometric Systems-2

Sl No	Author	Year	Method	Modalities	Dataset	Metric	Accuracy	Limitation
1	Cherrat et al. [7]	2020	Gabor filter, HOG, CNN, SVM, Decision fusion	Fingerprint, Finger vein, Face	FVC2004, VERA Fingervein Database, AR face database	Accuracy	99.43%	Need for larger datasets
2	Mustafa et al. [5]	2020	GLCM, KNN, Decision fusion	Iris, Fingerprint	CASIA-Iris V1 & V2, FVC2004	Recognition accuracy	90%	Lack of preprocessing
3	Mehdi et al. [8]	2020	CNN, Softmax, RF, Fusion	Fingerprint, Finger vein, Face	SDUMLA-HMT	Accuracy	99.49%	Limited dataset testing
4	Sengar et al. [9]	2020	DNN, MLP, Back-propagation, Minutiae matching	Fingerprint, Palm-print	Inhouse database	FAR, FRR	97.60%	Noise in images, Dataset size
5	Zhang et al. [10]	2020	Haar cascades, LBP, Improved VAD, Adaptive fusion	Face, Voice	XJTU multi-modal, GT_DB, TIMIT	Accuracy	98%	Hardware limitations
6	El_Rahman et al. [11]	2020	ECG and Fingerprint fusion, Different classifiers	ECG, Fingerprint	MIT-BIH, FVC2004	ROC, AUC, Sensitivity, Specificity, Efficiency	99.43%	Limited modalities
7	Byahatti et al. [4]	2020	Log Gabor, LBP, MFCC, LPC, Fusion	Face, Voice	Self-collected, AR database	Accuracy, FAR, FRR, ROC	100%	Optimization of fused features
8	Zhang et al. [12]	2020	RNN, EEG, Gait, Fusion	EEG, Gait	GT_DB, TIMIT	FAR, FRR	0%, 1%	Device usability, Lab setting requirement
9	Purohit et al. [13]	2021	Oppositional Grasshopper Optimization Algorithm, Multi-Kernel SVM	Fingerprint, Ear, Palm	IIT Delhi ear database, CASIA	Accuracy	91.6%	Dimensionality and redundancy in feature vectors
10	Lee et al. [14]	2021	Multi-modal Extended Feature Vector (MEFV) Hashing	Face, Fingerprint	FVC2002, FVC2004, LFW	EER	2.32%	Privacy concerns, Attack model limitations
11	Kamlaskar et al. [15]	2021	Canonical correlation analysis (CCA)	Iris, Fingerprint	SDUMLA-HMT	EER	1.42%	Segmentation and central point detection accuracy
12	Vijay et al. [16]	2021	Score level fusion, CEWA algorithm	Ear, Finger vein, Iris	SDUMLA-HMT, AMI Ear	Accuracy, Sensitivity, Specificity	95.36%	Dataset bias, Illumination variations
13	Labayen et al. [17]	2021	Multi-biometric continuous authentication	Face, Voice, Typing	Inhouse Dataset	Accuracy, FAR, FRR	94.25%	Variance in face pose and light, Monitoring scope
14	Leghari et al. [18]	2021	Convolutional Neural Network (CNN)	Fingerprint, On-line signature	Inhouse Dataset	Accuracy	99.10%	Security concerns, Limited data
15	Cherifi et al. [19]	2021	Random Forest classifier, Score-level fusion	Ear, Arm gesture	AWE, HMOG database	EER	0.30%	Noisy biometric data, Real-world deployment conditions
16	Conti et al. [20]	2021	Levenshtein distance (LD)	Iris, Retina	DRIVE retina database, University of Bath iris database	DET curves, FAR, FRR	3.33%	Absence of joint retina-iris databases
17	Omotosho et al. [1]	2021	Convolutional Neural Network (CNN)	Face, Iris	CASIA iris	Accuracy	98.33%	Larger dataset experimentation
18	Xiong et al. [21]	2021	Modified chaotic binary particle swarm optimization (MCBPSO)	Face, Iris	CASIA multimodal iris and face dataset	Recognition rate	99.78%	Limited iris image variation
19	Medjahed et al. [22]	2022	CNN, KNN	Face, Left and Right Palm prints	FEI face dataset, IITD palm print database	Accuracy	99.28% (clean), 97.14% (noisy)	Image resolution impact not evaluated
20	Tyagi et al. [23]	2022	CNN-based feature extraction, Score level fusion	Face, Finger vein	Finger Vein Recognition (FVR) dataset	Identification Accuracy, EER, ROC curve	100%	Additional hardware costs
21	El-Rahiem et al. [24]	2022	Deep fusion, MCCA, Feature and score fusion	ECG, Finger vein	VeinPolyU finger vein, TW finger vein, MWMHIT, ECG-ID	EER	0.12% (feature fusion), 1.40% (score fusion)	Lack of large dataset
22	Wang et al. [25]	2022	Fusion Conv, Self-attention mechanism, Concat	Finger vein, Face	SDUMLA-FV, FV-USM, CASIA-WebFace	Accuracy	87.57% - 98.4%	Small sample size, Limited biometric modalities
23	Ahamed et al. [26]	2022	Naive Bayes, LSTM, CNN	ECG, PPG	Public datasets (PhysioNet, Mendeley)	Accuracy, EER	99.8%, 0.16	Excludes other biometric modalities, Need for larger dataset
24	Vyas et al. [3]	2022	Bit-transition code, Score-level fusion	Iris, Palmprint	IITD iris, PolyU palmprint database	EER, AUC	99.92%	Lack of extensive experimentation
25	Iula et al. [27]	2022	Score level fusion	3D Ultrasound Palmprint, Hand geometry	Homemade database	Accuracy	100%	Not explicitly stated
26	Goh et al. [28]	2022	Index-of-Max hashing, AFH, Feature-level fusion	Various biometric modalities	FVC2002, CASIA, UTFVP	EER	1.82%	Dealing with unaligned templates
27	Joseph et al. [29]	2022	CNN, ORB, Score level fusion	Face, Fingerprint	UCI	Accuracy	96%	Imbalanced dataset, Scope for improvement
28	Elisha et al. [30]	2022	DWT, SVD, Logic OR	Face, Fingerprint, Iris	ORL, AT&T, FVC2002	Accuracy, Recognition rate	98%, 100%	Greater sample storage, Lighting conditions
29	Elisha et al. [30]	2022	DWT, SVD, Logic OR	Face, Fingerprint, Iris	ORL, AT&T, FVC2002	Accuracy, Recognition rate	98%, 100%	Greater sample storage, Lighting conditions
30	Ipeayeda et al. [31]	2023	GWGSA	Face, Fingerprint, Iris	Inhouse datasets	Recognition Accuracy	97.76%	Not effective for weakly correlated features, High computational complexity
31	Safavipour et al. [32]	2023	Fusion Conv, RKHS, Quaternion-based, Deep FC	Face, Iris, Fingerprint	FERET, Shahed-University, CASIA	Accuracy	100%	Noise, Poor data quality, Non-universality, Large variations
32	Micucci et al. [2]	2023	Weighted score sum rule	Hand geometry, Palm-print	Homemade database	EER	0.06% (EER), 100% (identification)	Small dataset size
33	Singh et al. [33]	2023	WOA-ANN, SSA-DBN	ECG, Sclera, Fingerprint	MIT-BIH Arrhythmia, Sclera: SBVPI	Accuracy	97.13%	Data corruption, Large-scale scenarios
34	Balogun et al. [34]	2023	ONSA	Face, Fingerprint, Iris, Voice, Signature	Inhouse dataset	Accuracy, FRR, FAR	98.33%	Non-real dataset, Limited samples
35	Vasavi et al. [35]	2023	RDCNN	Iris, Palm print, Lip	460 iris, 100 palm print, 100 lip images	Accuracy, Precision, Recall, F1-score	97%	Combining multiple modalities
36	Alharbi et al. [36]	2023	GMM, FaceNet, Score level fusion	Voice, Face	VCTK, VoxCeleb	EER	1.62%	Small dataset size, Need for further evaluation
37	Salama et al. [37]	2023	EEG, Optical encryption, Watermarking	EEG, Biometric images	EEGMAT, ORL, FVC 2002 DB1, CASIA-V3, CASIA-V1	EER, FAR, FRR, AROC	Close to 0 EER, Close to 1 AROC	Dependence on signal quality, Dataset size
38	Coelho et al. [38]	2023	CNN, FL	PPG, ECG	CapnoBase, BIDMC, TROIKA	Accuracy, FAR, FRR	99.27%	Limited availability of health data, Data heterogeneity
39	Kazi et al. [39]	2023	Score/Decision fusion	Face, Fingerprint, Signature	YALE-FVC2002KVKR	Accuracy	99.04%	Noisy data, Spoof attacks, High error rates
40	El_Rahman et al. [40]	2024	CNN, Traditional methods	ECG, Fingerprint	MIT-BIH ECG, FVC2004 fingerprint	AUC, ROC curves, Precision, Sensitivity, Specificity	99%	Limited ECG databases, Virtual dataset limitations, Computational cost
41	Byeon et al. [41]	2024	Deep learning fusion	Iris, Fingerprint, Face	Simulated dataset	Accuracy	99.6%	Dataset reliability
42	Priyani et al. [42]	2024	HGSSA-bi LSTM	Iris, Fingerprint	CASIA dataset	Accuracy, Precision, F1-score, Sensitivity, Specificity	98.5%	Complexity, Cost, Variability
43	Samatha et al. [43]	2024	Decision-level fusion	Face, Fingerprint, Iris	Chicago Face, MMU1, SO-COfing	Accuracy	93%	Data distortion, Interclass similarities, Non-universality
44	Kadhim et al. [44]	2024	Database creation	Face	MULBv1	Accuracy	97.41%	Lack of critical qualities, Complexity in database creation
45	Gunasekaran et al. [45]	2024	Geometric Curvelet and Minkowski	Fingerprint, Face, Iris	CASIA Biometric Ideal Test Dataset	FAR	18%	Insufficient samples, Dataset comprehensiveness
46	Amin et al. [46]	2024	VGG19-SC fusion	Iris, Face	Digital camera dataset	Accuracy	99.39%	High implementation cost, Scalability
47	Subramaniam et al. [6]	2024	Convolutional Neural Network	Finger vein	STUMULA-HMT	Accuracy	99.83%	Intra-class variation, Noisy data
48	Parvathy et al. [47]	2024	FRMSDNET Classifier	Iris, Fingerprint	CASIA-IrisV3, Socofing	Accuracy	99.29%	Biometric recognition challenges
49	Liu et al. [48]	2024	FarSight system	Face, Gait, Body shape	BRIAR dataset	Verification, Identification	88%	Heavy reliance on deep learning, Limited 3D information

[4] P. Byahatti and M. S. Shettar, "Fusion strategies for multimodal biometric system using face and voice cues," in *IOP conference series: materials science and engineering*, vol. 925, no. 1. IOP Publishing, 2020, p. 012031.

[5] A. S. Mustafa, A. J. Abdulelah, and A. K. Ahmed, "Multimodal biometric system iris and fingerprint recognition based on fusion technique," *International Journal of Advanced Science and Technology*, vol. 29, no. 03, pp. 7423–7432, 2020.

[6] B. Subramaniam, S. V. Krishnan, S. Radhakrishnan, and V. E. Balas, "Fusion of finger vein images, at score level, for personal authentication," *Acta Polytechnica Hungarica*, vol. 21, no. 6, 2024.

[7] R. A. El mehdi Cherrat and H. Bouzahir, "A multimodal biometric identification system based on cascade advanced of fingerprint, fingervein and face images," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 18, no. 1, pp. 1562–1570, 2020.

[8] E. mehdi Cherrat, R. Alaoui, and H. Bouzahir, "Convolutional neural networks approach for multimodal biometric identification system using the fusion of fingerprint, finger-vein and face images," *PeerJ Computer Science*, vol. 6, p. e248, 2020.

[9] S. S. Sengar, U. Hariharan, and K. Rajkumar, "Multimodal biometric authentication system using deep learning method," in *2020 International Conference on Emerging Smart Computing and Informatics (ESCI)*. IEEE, 2020, pp. 309–312.

[10] X. Zhang, D. Cheng, P. Jia, Y. Dai, and X. Xu, "An efficient android-based multimodal biometric authentication system with face and voice," *IEEE Access*, vol. 8, pp. 102 757–102 772, 2020.

[11] S. A. El_Rahman, "Multimodal biometric systems based on different fusion levels of ecg and fingerprint using different classifiers," *Soft Computing*, vol. 24, pp. 12 599–12 632, 2020.

[12] X. Zhang, L. Yao, C. Huang, T. Gu, Z. Yang, and Y. Liu, "Deepkey: A multimodal biometric authentication system via deep decoding gaits and brainwaves," *ACM Transactions on Intelligent Systems and Technology (TIST)*, vol. 11, no. 4, pp. 1–24, 2020.

[13] H. Purohit and P. K. Ajmera, "Optimal feature level fusion for secured human authentication in multimodal biometric system," *Machine Vision and Applications*, vol. 32, no. 1, p. 24, 2021.

[14] M. J. Lee, A. B. J. Teoh, A. Uhl, S.-N. Liang, and Z. Jin, "A tokenless cancellable scheme for multimodal biometric systems," *Computers & Security*, vol. 108, p. 102350, 2021.

[15] C. Kamlaskar and A. Abhyankar, "Iris-fingerprint multimodal biometric system based on optimal feature level fusion model," *AIMS Electronics and Electrical Engineering*, vol. 5, no. 4, pp. 229–250, 2021.

[16] M. Vijay and G. Indumathi, "Deep belief network-based hybrid model for multimodal biometric system for futuristic security applications," *Journal of Information Security and Applications*, vol. 58, p. 102707, 2021.

[17] M. Labayen, R. Vea, J. Flórez, N. Aginako, and B. Sierra, "Online student authentication and proctoring system based on multimodal biometrics technology," *IEEE Access*, vol. 9, pp. 72 398–72 411, 2021.

[18] M. Leghari, S. Memon, L. D. Dhomeja, A. H. Jalbani, and A. A.

Chandio, "Deep feature fusion of fingerprint and online signature for multimodal biometrics," *Computers*, vol. 10, no. 2, p. 21, 2021.

[19] F. Cherifi, K. Amroun, and M. Omar, "Robust multimodal biometric authentication on iot device through ear shape and arm gesture," *Multimedia Tools and Applications*, vol. 80, no. 10, pp. 14 807–14 827, 2021.

[20] V. Conti, L. Rundo, C. Militello, V. M. Salerno, S. Vitabile, and S. M. Siniscalchi, "A multimodal retina-iris biometric system using the levenshtein distance for spatial feature comparison," *IET Biometrics*, vol. 10, no. 1, pp. 44–64, 2021.

[21] Q. Xiong, X. Zhang, X. Xu, and S. He, "A modified chaotic binary particle swarm optimization scheme and its application in face-iris multimodal biometric identification," *Electronics*, vol. 10, no. 2, p. 217, 2021.

[22] C. Medjahed, A. Rahmoun, C. Charrier, and F. Mezzoudj, "A deep learning-based multimodal biometric system using score fusion," *IAES Int. J. Artif. Intell*, vol. 11, no. 1, p. 65, 2022.

[23] S. Tyagi, B. Chawla, R. Jain, and S. Srivastava, "Multimodal biometric system using deep learning based on face and finger vein fusion," *Journal of Intelligent & Fuzzy Systems*, vol. 42, no. 2, pp. 943–955, 2022.

[24] B. A. El-Rahiem, F. E. A. El-Samie, and M. Amin, "Multimodal biometric authentication based on deep fusion of electrocardiogram (ecg) and finger vein," *Multimedia Systems*, vol. 28, no. 4, pp. 1325–1337, 2022.

[25] Y. Wang, D. Shi, and W. Zhou, "Convolutional neural network approach based on multimodal biometric system with fusion of face and finger vein features," *Sensors*, vol. 22, no. 16, p. 6039, 2022.

[26] F. Ahamed, F. Farid, B. Suleiman, Z. Jan, L. A. Wahsheh, and S. Shahrestani, "An intelligent multimodal biometric authentication model for personalised healthcare services," *Future Internet*, vol. 14, no. 8, p. 222, 2022.

[27] A. Iula and M. Micucci, "Multimodal biometric recognition based on 3d ultrasound palmprint-hand geometry fusion," *IEEE Access*, vol. 10, pp. 7914–7925, 2022.

[28] Z. H. Goh, Y. Wang, L. Leng, S.-N. Liang, Z. Jin, Y.-L. Lai, and X. Wang, "A framework for multimodal biometric authentication systems with template protection," *IEEE Access*, vol. 10, pp. 96 388–96 402, 2022.

[29] A. A. Joseph, A. Ng Ho Lian, K. Kipli, K. L. Chin, D. A. A. Mat, C. Sia Chin Voon, D. Chua Sing Ngie, and N. S. Song, "Person verification based on multimodal biometric recognition." *Pertanika Journal of Science & Technology*, vol. 30, no. 1, 2022.

[30] B. Elisha Raju, K. Ramesh Chandra, and P. R. Budumuru, "A two-level security system based on multimodal biometrics and modified fusion technique," in *Sustainable Communication Networks and Application: Proceedings of ICSCN 2021*. Springer, 2022, pp. 29–39.

[31] F. W. Ipeayeda, M. O. Oyediran, S. A. Ajagbe, J. O. Jooda, and M. O. Adigun, "Optimized gravitational search algorithm for feature fusion in a multimodal biometric system," *Results in Engineering*, vol. 20, p. 101572, 2023.

[32] M. H. Safavipour, M. A. Doostari, H. Sadjedi *et al.*, "Deep hybrid

multimodal biometric recognition system based on features-level deep fusion of five biometric traits," *Computational Intelligence and Neuroscience*, vol. 2023, 2023.

[33] S. P. Singh and S. Tiwari, "A dual multimodal biometric authentication system based on woa-ann and ssa-dbn techniques," *Sci*, vol. 5, no. 1, p. 10, 2023.

[34] M. O. Balogun, L. A. Odeniyi, E. O. Omidiora, S. O. Olabiyisi, A. S. Falohun *et al.*, "Optimized negative selection algorithm for image classification in multimodal biometric system," *Acta Informatica Pragensia*, vol. 12, no. 1, pp. 3–18, 2023.

[35] J. Vasavi and M. Abirami, "Novel multimodal biometric feature extraction for precise human identification." *Intelligent Automation & Soft Computing*, vol. 36, no. 2, 2023.

[36] B. Alharbi and H. S. Alshanbari, "Face-voice based multimodal biometric authentication system via facenet and gmm," *PeerJ Computer Science*, vol. 9, p. e1468, 2023.

[37] G. M. Salama, S. El-Gazar, B. Omar, and A. Hassan, "Multimodal cancelable biometric authentication system based on eeg signal for iot applications," *Journal of Optics*, pp. 1–15, 2023.

[38] K. K. Coelho, E. T. Tristão, M. Nogueira, A. B. Vieira, and J. A. Nacif, "Multimodal biometric authentication method by federated learning," *Biomedical Signal Processing and Control*, vol. 85, p. 105022, 2023.

[39] M. Kazi, K. Kale, R. S. Mehsen, A. Mane, V. Humbe, Y. Rode, S. Dabhade, N. Bansod, A. Razvi, and P. Deshmukh, "Face, fingerprint, and signature based multimodal biometric system using score level and decision level fusion approaches," *IETE Journal of Research*, pp. 1–20, 2023.

[40] S. A. El_Rahman and A. S. Alluhaidan, "Enhanced multimodal biometric recognition systems based on deep learning and traditional methods in smart environments," *Plos one*, vol. 19, no. 2, p. e0291084, 2024.

[41] H. Byeon, V. Raina, M. Sandhu, M. Shabaz, I. Keshta, M. Soni, K. Matrouk, P. P. Singh, and T. Lakshmi, "Artificial intelligence-enabled deep learning model for multimodal biometric fusion," *Multimedia Tools and Applications*, pp. 1–24, 2024.

[42] J. Priyani, P. Nanglia, P. Singh, V. Shokeen, and A. Sharma, "Hgssa-bi lstm: A secure multimodal biometric sensing using optimized bi-directional long short-term memory with self-attention," *ECS Sensors Plus*, vol. 3, no. 1, p. 011401, 2024.

[43] J. Samatha and G. Madhavi, "Securesense: Enhancing person verification through multimodal biometrics for robust authentication," *Scalable Computing: Practice and Experience*, vol. 25, no. 2, pp. 1040–1054, 2024.

[44] O. N. Kadhim and M. H. Abdulameer, "A multimodal biometric database and case study for face recognition based deep learning," *Bulletin of Electrical Engineering and Informatics*, vol. 13, no. 1, pp. 677–685, 2024.

[45] K. Gunasekaran, J. Raja, R. Pitchai, and M. Dhurgadevi, "Human multimodal biometric recognition using rationalized adaboost and geometric curvelet," *International Journal of Computing and Digital Systems*, vol. 15, no. 1, pp. 1–13, 2024.

[46] P. Amin, D. Ganesh, A. Gantra, and P. Singhal, "Improved human identification by multi-biometric image sensor integration with a deep learning approach," 2024.

[47] J. Parvathy and P. G. Patil, "Frmsdnet classifier for multimodal feature fusion biometric authentication," *International Journal of Intelligent Systems and Applications in Engineering*, vol. 12, no. 6s, pp. 169–186, 2024.

[48] F. Liu, R. Ashbaugh, N. Chimitt, N. Hassan, A. Hassani, A. Jaiswal, M. Kim, Z. Mao, C. Perry, Z. Ren *et al.*, "Farsight: A physics-driven whole-body biometric system at large distance and altitude," in *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, 2024, pp. 6227–6236.

Diptadip Maiti , is currently a research scholar in the department of Computer Science & Engineering at Techno India University, West Bengal. He did his B. Tech. in Computer Science & Engineering and M. Tech in Information Technology in 2005 and 2009 respectively. His research interests are in Image Processing, Biometric Authentication, Machine Learning and Deep Learning.

Madhuchhanda Basak , is currently a research scholar in the department of Computer Science & Engineering at Techno India University, West Bengal. She did his B. Tech. & M. Tech. in Information Technology in 2006 and 2010 respectively. Her research interests are in Image Processing, Biometric Authentication, Machine Learning and Deep Learning.

Debashis Das , is an Associate Professor in the department of Computer Science & Engineering at Techno India University, West Bengal. He did his B. Tech. in Information Technology and M. Tech in Computer Science & Engineering in 2009 and 2012 respectively. He did his PhD in Computer Science & Engineering in 2017. His research interests are in Image Processing, Biometric Authentication and Steganography.