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# Multimodal biometric integration: Trends and insights from the past quinquennial

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## 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 behavioral 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.

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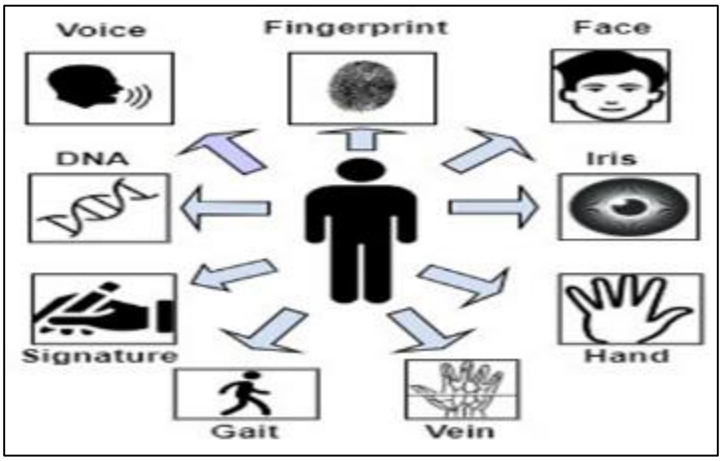



**Figure 1** Biometric traits

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

**Table 1** Comparison of Different Unimodal & Multimodal Bio-Metric Traits

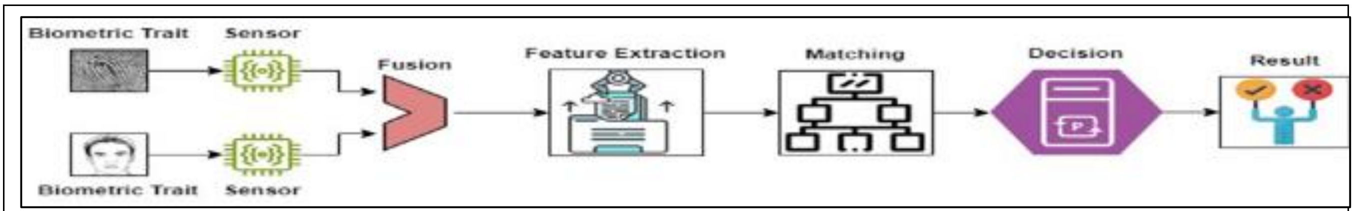
| BIOMETRIC | Mode | DISTINCTIVENESS | PERFORMANCE | COLLECTIVITY | ACCEPTABILITY | UNIVERSALITY | CIRCUMVENTION | COST | ACCURACY | REQUIRED DEVICE | USERFRIENDLINESS |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Fingerprint | Unimodal | High | High | High | Medium | Medium | Low | Medium | 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 |

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]. Figure 2 represents different multimodal biometric systems.

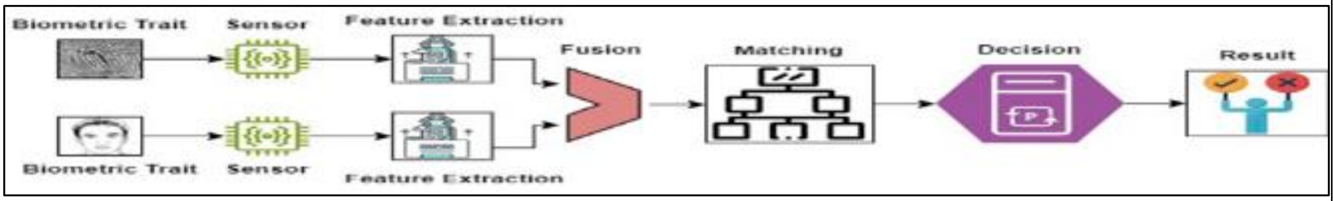
In this research, we delve into the various advancements and cutting-edge techniques within the realm of multimodal biometrics. After the introduction in the section 1, the paper is organized as follows: Section 2 delves into the historical evolution of multimodal biometrics over the past five years.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

### 1.1. Evolution of Multimodal Biometric

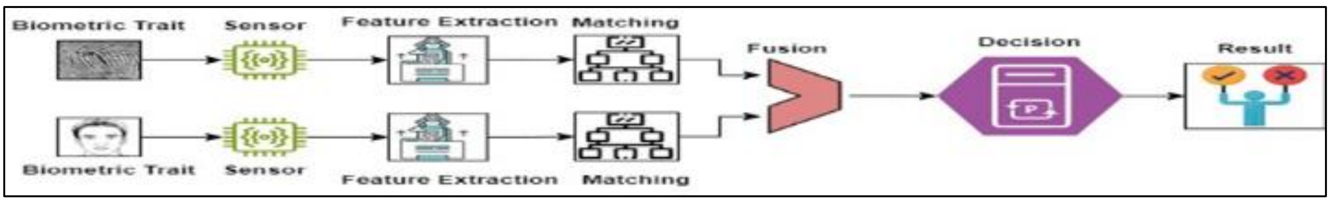
Using cutting-edge methods and decision-level fusion, Cherrat et al. [7] provide a multi-modal biometric system combining fingerprint, finger vein, and facial pictures. By using CNN, SVM classifier, Gabor filter, and linear regression line, the system outperforms single biometric systems with an accuracy 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



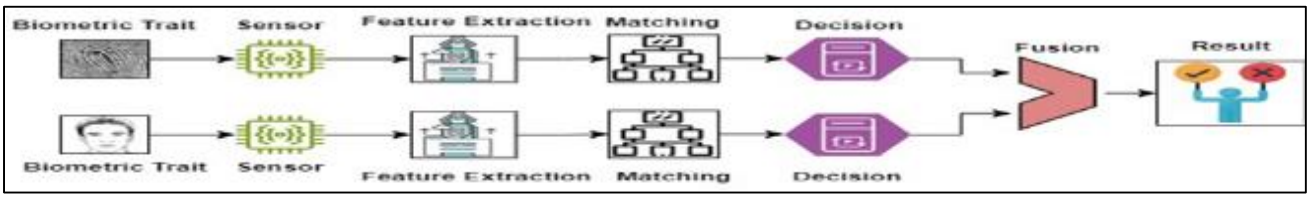

Sensor label fusion



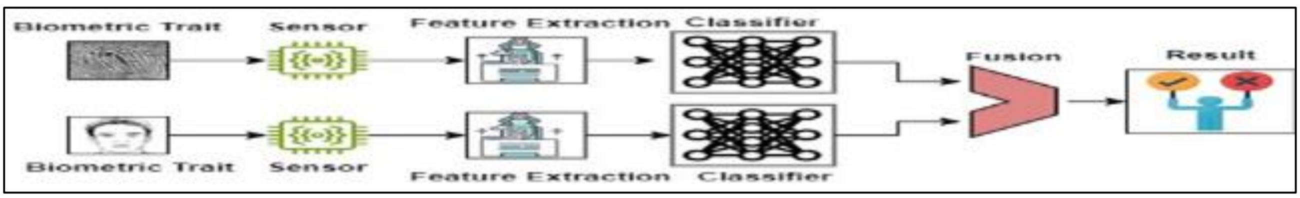

Feature label fusion



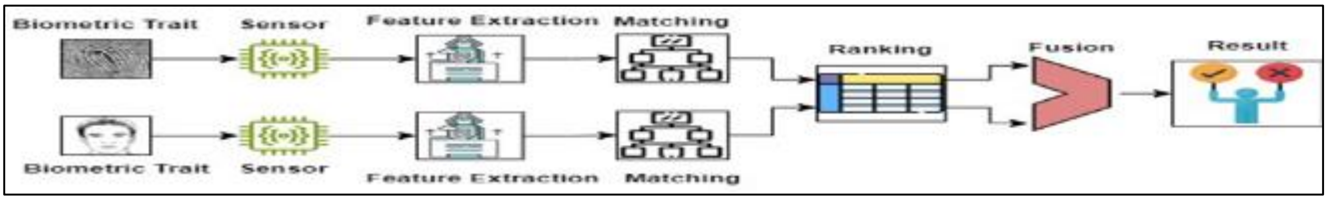

Score label fusion




Decision label fusion



Classifier label fusion




Rank label fusion

**Figure 2** Multimodal Biometric fusion techniques

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 unimodal 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 unimodal systems using a variety of fusion strategies and classifiers.

In contrast to unimodal 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 with different fusion levels. Sequential and parallel multi-modal 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 multi-modal database, the performance outperforms unimodal 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 Deep Key, a multi-modal biometric authentication system that combines gait and EEG modalities. Beaten by baseline models and cutting-edge techniques, Deep Key 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 token less 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 unimodal 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 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 Vox Celeb 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.

## 2. 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%.

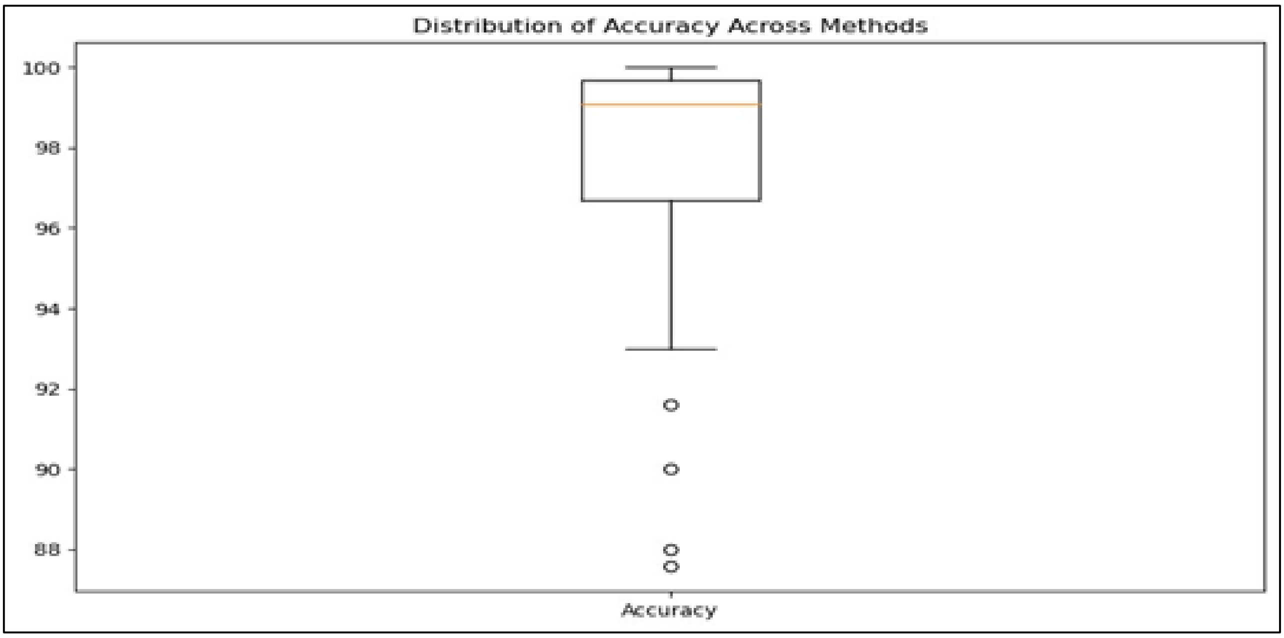



**Figure 3** Distribution of accuracy across methods

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.

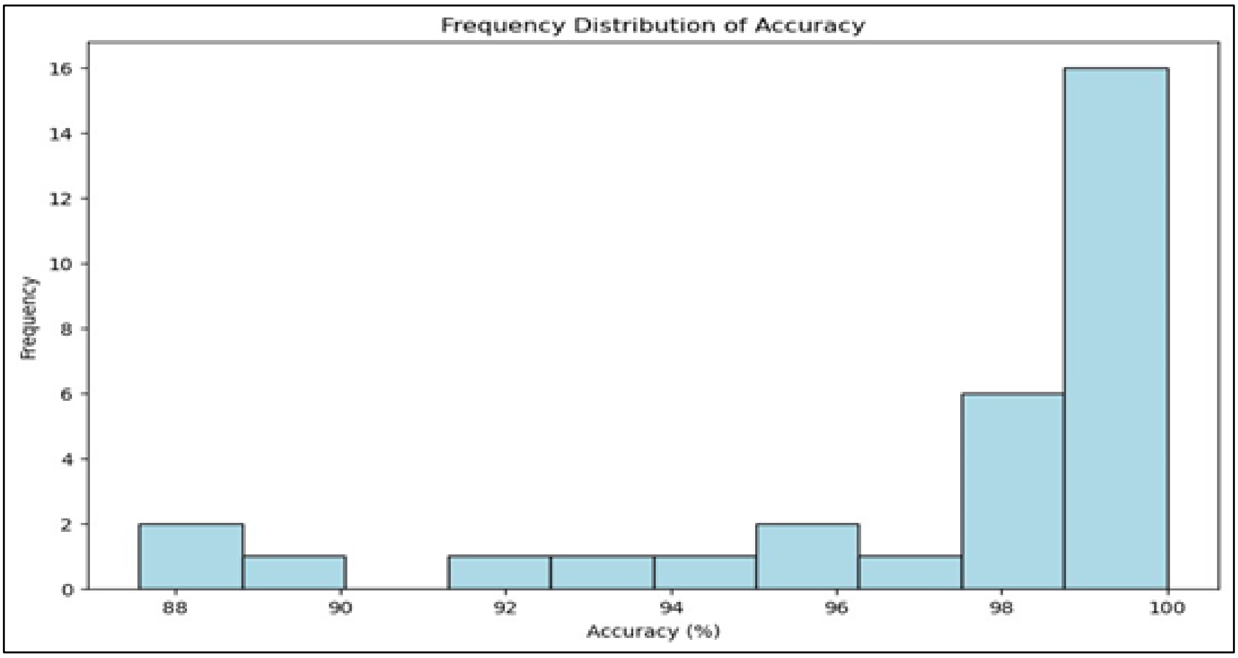



**Figure 4** Frequency distribution of accuracy

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 suffer from limited dataset which eventually ask the generalization of the methods for practical implementation. Only combination of few modalities has been studied by almost 31% methods. Around 19% methods suffer 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.

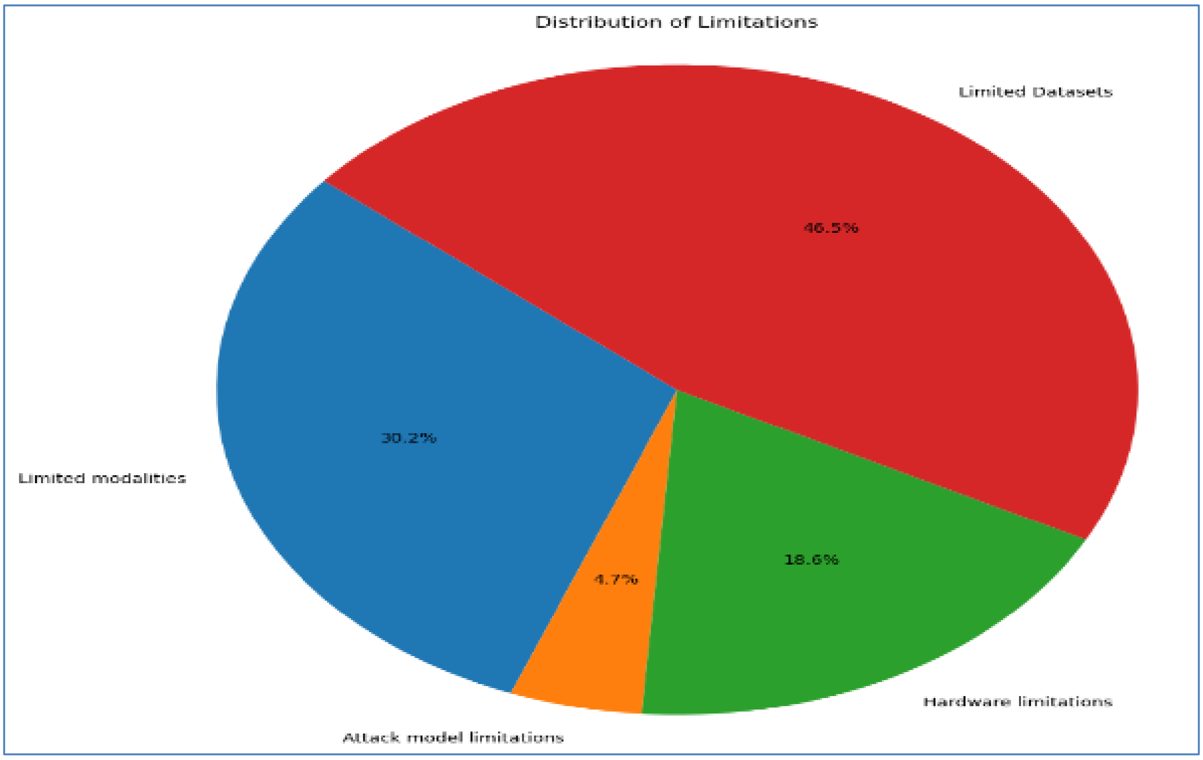



**Figure 5** Distribution of limitations

**Table 2** 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 Finger vein 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 |

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| 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% | 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, ECGID | 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 |

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| 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 | Ipeayeda et al. [31] | 2023 | GWGSA | Face, Fingerprint, Iris | Inhouse datasets | Recognition Accuracy | 97.76% | Not effective for weakly correlated features, High computational complexity |
| 30 | Safavipour et al. [32] | 2023 | Fusion Conv, RKHS, Quaternionbased, Deep FC | Face, Iris, Fingerprint | FERET, Shahed-University, CASIA | Accuracy | 100% | Noise, Poor data quality, Nonuniversality, Large variations |
| 31 | Micucci et al. [2] | 2023 | Weighted score sum rule | Hand geometry, Palm-print | Homemade database | EER | 0.06% (EER), 100% (identifi-cation) | Small dataset size |
| 32 | 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 |
| 33 | Balogun et al. [34] | 2023 | ONSA | Face, Fingerprint, Iris, Voice, Signature | Inhouse dataset | Accuracy, FRR, FAR | 98.33% | Non-real dataset, Limited samples |
| 34 | 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 |
| 35 | Alharbi et al. [36] | 2023 | GMM, FaceNet, Score level fusion | Voice, Face | VCTK, VoxCeleb | EER | 1.62% | Small dataset size, Need for further evaluation |
| 36 | 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 |
| 37 | Coelho et al. [38] | 2023 | CNN, FL | PPG, ECG | CapnoBase, BIDMC, | Accuracy, FAR, FRR | 99.27% | Limited availability of health data, Data heterogeneity |

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| 38 | Kazi et al. [39] | 2023 | Score/Decision fusion | Face, Fingerprint, Signature | YALE-FVC2002KVKR | Accuracy | 99.04% | Noisy data, Spoof attacks, High error rates |
| 39 | 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 |
| 40 | Byeon et al. [41] | 2024 | Deep learning fusion | Iris, Fingerprint, Face | Simulated dataset | Accuracy | 99.6% | Dataset reliability |
| 41 | Priyani et al. [42] | 2024 | HGSSA-bi LSTM | Iris, Fingerprint | CASIA dataset | Accuracy, Precision, F1-score, Sensitivity, Specificity | 98.5% | Complexity, Cost, Variability |
| 42 | Samatha et al. [43] | 2024 | Decision-level fusion | Face, Fingerprint, Iris | Chicago Face, MMU1, SOCOfing | Accuracy | 93% | Data distortion, Interclass similarities, non-universality |
| 43 | Kadhim et al. [44] | 2024 | Database creation | Face | MULBv1 | Accuracy | 97.41% | Lack of critical qualities, Complexity in database creation |
| 44 | Gunasekaran et al. [45] | 2024 | Geometric Curvelet and Minkowski | Fingerprint, Face, Iris | CASIA Biometric Ideal Test Dataset | FAR | 18% | Insufficient samples, Dataset comprehensiveness |
| 45 | Amin et al. [46] | 2024 | VGG19-SC fusion | Iris, Face | Digital camera dataset | Accuracy | 99.39% | High implementation cost, Scalability |
| 46 | Subramaniam et al. [6] | 2024 | Convolutional Neural Network | Finger vein | STUMULA-HMT | Accuracy | 99.83% | Intra-class variation, Noisy data |
| 47 | Parvathy et al. [47] | 2024 | FRMSDNET Classifier | Iris, Fingerprint | CASIA-IrisV3, Socofing | Accuracy | 99.29% | Biometric recognition challenges |
| 48 | Liu et al. [48] | 2024 | FarSight system | Face, Gait, Body shape | BRIAR dataset | Verification, Identification | 88% | Heavy reliance on deep learning, Limited 3D information |

## 3. 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.

## Compliance with ethical standards

### *Disclosure of conflict of interest*

No conflict of interest to be disclosed.

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