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Synergistic Approaches in Multimodal Biometric Authentication with Machine Learning and Deep Learning Paradigms

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Abstract: Biometric authentication systems have become crucial for ensuring secure access to a wide range of services and resources in our digital age. Conventional user authentication methods may fall short of the requirements for safeguarding against unauthorized access during data collection, storage, and transmission. Consequently, there is a demand for the advancement of technologies that enable user authentication based on distinctive personal identifiers, specifically biometric characteristics. Common biometric modalities include face, iris scans, palm prints, fingerprints, and voices, However, there are plenty of other biometrics, including DNA, ear scans, retinal scans, stride, and even behavioral patterns. One biometric modality (uni-modal biometrics) or a combination of several modalities (multi-modal biometrics) can be used for automated person identification. This paper offers a thorough review of the literature on various fusion techniques used in multi-modal biometrics. In addition, we provide a comparative study of advanced systems on a range of criteria and end the paper with appropriate recommendations for future work.

Keywords: *Biometric Fusion levels, Convolutional Neural Networks, Deep Learning, Multi-Modal Biometric System,*

1. Introduction

The field of unique identification is changing; computer-aided devices are being treated as a more sophisticated and secure means of identification. One of the most dependable features that can be utilized for individual recognition is biometrics. Conventional identification techniques, like ID cards and passwords [1,2], have been used to manage restricted system access. These techniques can be exploited by fraudulent attempts or unauthorized individuals, making them vulnerable. As a result of the difficulties associated with conventional approaches, biometrics is becoming more and more popular. Biometric systems automatically identify people based on physiological and behavioral attributes such as hand geometry, iris, fingerprints, facial features, voice, retina, palm print, stride pattern, signature, and keystroke dynamics. [3]. Fig. 1 illustrates the ontology of different authentication approaches, with biometric traits [4].

Two kinds of biometrics can be made specific, multimodal, and unimodal. Unimodal biometric systems are designed to recognize only a single trait, and th ey face several difficulties, including noisy data from sensors, non-universality, the selected biometric trait's lack of distinctiveness, high error rates, and vulnerability to spoof attacks [5]. In contrast, Biometric modalities such as voice, fingerprint, and face are integrated or fused in multi-modal biometric systems [6]. This integration improves the identification process' accuracy by utilizing complementary information from each modality. Applications for multi-modal systems can be found in banking, fraud detection, security and surveillance, continuous authentication, and other areas. Evaluating a user's preferred audio and visual formats can enhance the overall experience and boost customer satisfaction. Moreover, the amalgamation of aesthetic biometrics research with the development of emotionally intelligent robots can enhance client contentment and create novel prospects for investigation within the digital human research field.

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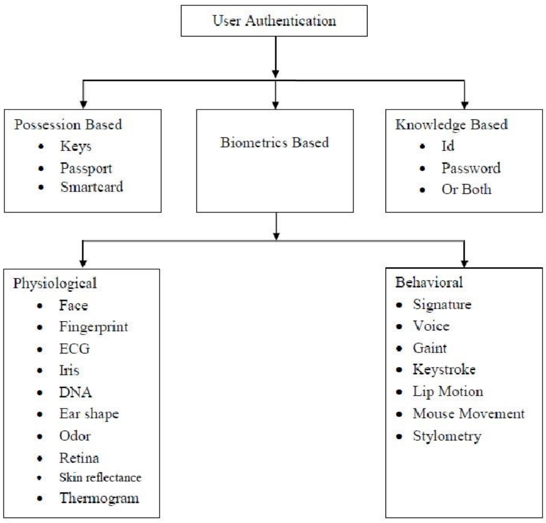

Fig. 1. Different types of authentication approaches [4]

This paper covers an overview of recently developed multi-modal biometric authentication systems based on deep learning and machine learning methods. We provide a comparative analysis of existing systems and suggest research directions based on the findings from literature surveys. The paper focuses on a deep literature survey on multimodal systems for biometric authentication with comparative analysis in Section II. Section III discusses findings concerning pros, cons, and scope for future enhancement. Section IV Concludes the paper and also provides research directions that can be considered for enhancement of current multi-modal systems.

2. Literature Survey

Authors in [7] suggested a multimodal biometric verification method that integrates the modalities of finger vein and (electrocardiogram) ECG. The system consists of three key components: biometric pre-processing, deep feature extraction, and verification. Each biometric was pre-processed using standardization and separation techniques, and features were retrieved using a suggested deep (Convolution Neural Network) CNN model [8–10]. Following that, the collected features were subjected to verification using five popular AI classifiers: K-Nearest Neighbors (KNNs), Support Vector Machine (SVM), Naive Bayes (NB), Random Forest (RF), and Artificial Neural Network (ANN). To expedite the verification process and handle deep features in a low-dimensional feature space, the authors implemented multi-set canonical correlation analysis or MCCA. The verification performance improved in the experimental findings, with EERs for score fusion and feature fusion of 1.40% and 0.12%, respectively.

Researchers in [8] examined (electroencephalographic) EEG signals to look for distinctive characteristics brought about by the thought and execution of four distinct upper limb movements. The usefulness and validity of these motor imagery tasks in creating a reliable multimodal biometric system for people with motor impairments were assessed. Ten participants in the study raised their left and right hands and made fists both in real life and in imagination. For both hypothetical and real activities, the suggested system produced a false acceptance rate of less than 2%. A novel multimodal strategy integrating multiple motor imagery tasks was executed with 98.28% precision, showcasing the usefulness of the shown biometric system for people with restricted motor skills or damaged motor abilities. Authors in [9] created an extremely reliable and entirely covert multimodal authentication system that uses the biometric modalities of the ear and arm signals to automatically authenticate users based on how they answer the phone. The authors present a novel method based on picture discontinuity that improves ear recognition robustness against occlusion to solve issues encountered by ear and arm signal verification systems in practical applications. Local Phase Quantization (LPQ) was used in ear feature extraction to provide pose and illumination variation robustness. In addition, four statistical measures were created to extract features from signals containing arm motion. With an (Equal Error Rate) EER of 5.15%, the multimodal biometric system was successful.

Authors in [10] proposed an effective feature selection algorithm for multimodal biometric verification using CASIA dataset images. Feature extraction utilized various techniques, and the balanced support feature selection algorithm was employed to enhance performance by rejecting irrelevant features or selecting optimal ones.

The authors of [11] presented a multimodal system that combined fingerprints and heartprints and included heartprint records with automatically updated templates. A small number of researchers [11,12] used a step-by-step technique to fuse fingerprints with heart prints to strengthen fingerprint authentication's resistance against presentation attacks. Deep learning, particularly CNNs, was explored for feature-level fusion, showing promising results in authentication tasks. The authors in [13, 14] merged fingerprints and heartprints. After extracting features from each modality independently using CNNs, internal fusion was used to create biometric templates that a classifier used for authentication. A multimodal biometric strategy for presentation assault detection was reported by researchers in [15].

Researchers investigate kernel Canonical Correlation Analysis (KCCA) for feature fusion in the cited article [16], hoping to find a nonlinear subspace learning representation between profile face and auditory modalities. The goal of this technique is to improve Canonical Correlation Analysis's (CCA) classification task performance. A supervised local-preserving Canonical Correlation Analysis method (SLPCCAM) is presented especially for fingerprint and finger vein modalities to further improve classification performance [17]. SLPCCAM enhances feature fusion efficacy by emphasizing the monitored maintenance of local structures.

The paper [18] presents a feature-level fusion strategy based on Discriminant Correlation Analysis (DCA) in the context of Iris, Fingerprint, and Face multimodal identification. The purpose of this method is to assess the dissimilarity between samples from various classes and offer a reliable depiction of the similarity within the same class. The article [19] examines a feature fusion method based on Multiset Generalized Canonical Discriminant Projection (MGCDP) for scenarios involving several sets of features. This approach is used for face, fingerprint, and palm vein modalities and includes class relationships. According to experimental data, MGCDP performs well in multimodal environments in terms of recognition accuracy.

Alay et al. [20] have developed an identification system that utilizes a deep learning algorithm to identify people through facial, iris, and finger vein biometrics. Convolutional neural networks are the foundation of the system's architecture (CNNs) employing the VGG-16 pre-trained model, Adam optimization, softmax classifier, and cross-entropy loss function. The CNN models for the face, iris, and finger vein are integrated, and image enhancement and dropout techniques are applied to prevent overfitting. Fusion strategies, including feature- and score-level fusion, are employed to investigate their effects on recognition performance. Using the SDUMLA-HMT dataset, the proposed system achieves an accuracy of 100% with feature-level fusion and 99.39% with score-level fusion, outperforming other state-of-the-art techniques.

Garg et al. [21] use speech, iris, and signature in multi-modal biometric fusion to improve recognition security. For every biometric, distinct classification mechanisms are introduced, and the features gathered from each categorization are combined. Various feature extraction methods are used, including the Scale Invariant Feature Transform (SIFT) for signatures, the Mel-frequency spectral coefficients for voice, and the two-dimensional principal component analysis (2DPCA) for iris. Artificial Neural Networks (ANN) are utilized for classification, and genetic algorithms (GA) are employed for feature optimization. The suggested method attains improved accuracy.

Sengar et al. [22] propose a multi-modal biometric solution using palm print and fingerprint data for authentication. The automated fingerprint identification system (AFIS) is employed, and the method achieves secure and unique identification by leveraging the richness of information in palms and fingerprints. Deep Neural Network (DNN) is used to enhance distinction accuracy, resulting in an accuracy rate of 97%.

In [23] propose a multi-modal biometric technique applying a fuzzy vault for palm prints, fingerprints, and hand veins recognition. Pre-processing involves removing undesirable elements and reducing noise levels using methods like median filtering and morphological operations. One feature vector point is produced via feature extraction, which combines chaff points and secret key points. Combining feature vector points and secret key points creates the fuzzy vault. Utilizing databases of palm prints, hand veins, and fingerprints, the experimental results show an enhanced recognition accuracy of 98.5%.

In Mahmoud et al. [24], an approach to multi-modal biometric identification is presented, which uses iris and facial traits to confirm an individual's identity. For person identification, the system combines traits from the left and right iris. Facial features are retrieved using the R-HOG (rectangle histogram of oriented gradient), and feature-level fusion adopts a unique fusion technique combining serial concatenation and canonical correlation. The deep belief network is a component of the recognition mechanism. In comparison to alternative outcomes, experimental results employing the SDUMLA-HMT database demonstrate a 34.5% reduction in fusion time.

Xinman Zhang et al. [25] develop a reliable system for Android-based facial and speech identification. To lower time and space complexity, the system uses an improved Local Binary Pattern (LBP) coding-based feature extraction technique. In low signal-to-noise ratio (SNR) conditions, algorithm performance is increased by an improved Voice Activity Detection (VAD) approach. By addressing the shortcomings of uni-modal authentication, adaptive fusion enhances multi-modal biometric fusion authentication. The system can successfully implement identity identification in a variety of high-security application settings, as shown by the experimental findings.

Abderrahmane et al. [26] offer a new score-level fusion method based on the weighted quasi-arithmetic mean (WQAM). Weighted mean and quasi-arithmetic mean features are combined to calculate WQAMs using a variety of trigonometric functions. There is no learning curve associated with this procedure. Tests conducted on openly accessible datasets demonstrate the efficacy of the suggested merging technique.

Rane and Bhadade [27] provide a matching score fusion method based on the t-norm for a multi-modal, heterogeneous biometric authentication system. Using facial and palm print traits, the algorithm extracts attributes and assigns a corresponding score to each trait. The t-norm-based score-level fusion greatly boosts accuracy. The method offers improved accuracy at both FAR levels, surpassing the performance of earlier research.

In Srivastava [28], A multi-modal biometric cryptography system employing individual fingerprints, finger veins and retina, is subjected to a realistic security examination. The system uses a combination strategy at the score level and uses RSA and the DNN order technique. The suggested framework considerably increases the performance of retinal, finger vein, and fingerprint acknowledgment verification, showing a 98.9% gain in GAR, 98.5% in accuracy, and a 0.05% drop in FAR compared to uni-modal biometric frameworks.

Using low- and high-frequency wavelet sub-bands, Devi and Rao [29] construct three decision-level fusion systems. When compared to uni-modal they demonstrate the biggest improvement in recognition rates. Iloanusi and Ejiogu [30] present a convolutional neural network architecture that can be used to identify a person's gender from their fingerprints. The results demonstrate that identifying a person's gender based on the fusion of five different right-hand finger types can improve performance. The top fusion model obtains accuracy rates of 94.7%, 88.0%, and 91.3% for men, women, and overall data, respectively. These reflect gains of 31.02%, 7.82%, and 18.72%.

Zhou et al. [31] present a hybrid fusion technique that combines an improved feature fusion algorithm with a special weighting vote strategy for a multi-modal biometric system. Experimental results on three different databases show improved precision and resilience over earlier research. Wajid et al. [32] developed a multi-modal biometric approach based on a fingerprint and a single palm, attaining an FRR of 2.25%, FAR of 2.0%, and TSR of 98.75%, using the IITD palm-print databases and UPEK fingerprint.

Yadav [33] presented a deep learning-based multi-modal human identification model that combined handwritten signatures, fingerprints, and iris data. With improved accuracy for feature-level fusion and score-level fusion on the SDUMLA-HMT dataset, the system which is based on convolutional neural networks (CNNs) displayed exceptional performance.

Kamlaskar and Abhyankar [34] suggested feature-level fusion for iris and fingerprint identification using Canonical Correlation Analysis (CCA), resulting in efficient multi-modal recognition with smaller feature sizes, streamlined calculations, and recognition durations of less than a second. When it came to equal error rate (EER), the suggested method fared better than unimodal systems.

Kumar et al. [35] introduced an Improved Biometric Fusion System (IBFS) that fuses features of face and fingerprint recognition, resulting in an increased performance with an average true positive rate of 99.8% and accuracy of 99.6%.

Vijayakumar et al. [36] created a multi-modal biometric authentication model that extracts features from the finger vein, palm print, iris, and face using CNN, resulting in precise and error-free identification. The work shows how deep learning models can be used to increase the testing scope by examining them in a multi-modal biometric system that is based on palm prints.

Arjun and Prakash et al. [37] proposed a hybrid model that combines various layers of multi-modal biometrics (facial and finger vein) utilizing decision-level and feature-level fusion algorithms. When compared to unimodal biometric systems, the suggested model, which used five classifiers for majority voting, demonstrated greater recognition rates.

Table 1 summarizes the multimodal biometric system studied during the literature survey based on the biometric features used, fusion approach, recognition algorithm, dataset, and performance evaluation metrics.

Table 1. Literature Survey Table

Biometric Features Used	***Fusion Methods***	***Recognition Algorithms***	***Datasets***	***Performance Evaluation***
Face, Finger Vein, Iris[20]	Feature- and Score-Level Fusion	CNN (VGG-16), Adam Optimization, Softmax Classifier	SDUMLA-HMT	Accuracy (100% with feature level, 99.39% with score level)
Speech, Iris, Signature[21]	Feature Fusion	Genetic Algorithms, Artificial Neural Networks	Not specified	Accuracy (96–98%)
Palm Print, Fingerprint[22]	Not specified	Deep Neural Network (DNN)	Not specified	Accuracy (97%)
Palm Print, Hand Veins, Fingerprints[23]	Feature Fusion	Fuzzy Vault, Median Filtering, Morphological Ops	Fingerprint, Hand Vein, Palm Print Databases	Recognition Accuracy (98.5%)
Iris, Facial Features[24]	Feature-Level Fusion	Deep Belief Network	SDUMLA-HMT	Fusion Time Reduction (34.5%), Recognition Accuracy (Up to 99%)
Voice, Face[25]	Adaptive Fusion	Local Binary Pattern (LBP), Voice Activity Detection	Not specified	Successful Identity Identification in Various Scenarios
Face, Palm Print[27]	Score-Level Fusion (t-norm)	Not specified	Not specified	GAR (99.7% at FAR 0.1%, 99.2% at FAR 0.01%)
Fingerprint, Retina, Finger Vein[28]	Score-Level Combination	RSA, DNN Order Approach	Not specified	Increase in GAR (98.9%), Accuracy (98.5%), Decrease in FAR (0.05%)
Fingerprints, Palm, Ear[29]	Decision-Level Fusion (Global, Local, Local-Global)	Wavelet Sub-Bands	Not specified	Maximum Increase in Recognition Rates (Up to 11.5%)
Fingerprints[30]	Not specified	Convolutional Neural Network (CNN)	Not specified	Accuracy Rates (Male: 94.7%, Female: 88.0%, Overall: 91.3%)
Palm, Fingerprint[32]	Not specified	Not specified	UPEK Fingerprint, IITD Palm-Print Databases	FRR (2.25%), FAR (2.0%), TSR (98.75%), Matching Time (1.90 seconds)

Iris, Fingerprint, Handwritten Signatures[33]	Feature- and Score-Level Fusion	Convolutional Neural Networks (CNNs)	SDUMLA-HMT	Accuracy (99.11% with feature level, 99.51% with score-level)
Face, Fingerprint[35]	Not specified	Improved Biometric Fusion System (IBFS)	Not specified	True Positive Rate (99.8%), Accuracy (99.6%)
Face, Iris, Palm Print, Finger Vein[36]	Not specified	CNN	Not specified	Accurate and Error-Free Identification
Face, Finger Vein[37]	Decision-Level and Feature-Level Fusion	Majority Voting with Five Classifiers	Not specified	Higher Recognition Rates compared to Unimodal Systems
Signature, Fingerprint[38]	Not specified	Deep Learning Neural Network Models	MCYT, SDUMLA-HMT Signature Databases	Positive Results in Effectiveness Evaluation
Face, Ear[39]	Not specified	Local Feature Descriptors, Kernel Discriminative Common Vector (KDCV)	Not specified	Improved Recognition Rates
Fingerprint, Ear, Palm[40]	Feature-Level Fusion	OGWO+LQ Algorithm, Multi-Kernel Support Vector Machine (MKSVM)	Not specified	Effectiveness of Fusion Technique
Finger Knuckle, Palm[41]	Not specified	Line Ordinal Pattern (LOP) Encoding, Non-Decimated Quaternion Wavelet	Not specified	Improved Recognition and Verification Performance
Finger Vein, Palm Print, DNA, Signatures, Hand shapes[42]	Multi-Level Fusion	Deep Learning Classification Algorithms	Diverse Multi-Modal Datasets	Accuracy (99.25% with score-level fusion on 3D ear and 3D face datasets)
Face, Fingerprint[43]	Feature-Level Fusion	Dis-Eigen Algorithm	Faces and Fingerprints from 20 People	Feature-Level Fusion Detection Rate (93.70%)
Face, Fingerprint[44]	Score-Level Fusion (Weighted Sum Rule)	ORB Algorithm, Convolutional Neural Network (CNN)	UCI Repository of Machine Learning Datasets	Encouraging Results in Person Recognition
Face, Palm Print, Fingerprint[45]	Score-Level Fusion (MIN, MAX, SUM)	SIFT, SURF	Not specified	Authentication Rate (95.08%), Surpassing Individual Rates

Channegowda et al. [38] created multi-modal biometric models using deep learning neural network models for recognition, incorporating features from fingerprints and signatures. Positive results were obtained from the study's evaluation of the suggested system's efficiency using the MCYT and SDUMLA-HMT datasets.

Sarangi et al. [39] addressed the drawbacks of ear biometrics by proposing a model based on face and ear profiles, achieving improved recognition rates through the integration of local feature descriptors and kernel discriminative common vector (KDCV) technique.

Purohit and Ajmera [40] suggested a productive feature-level fusion method that combines fingerprint, ear, and palm features for a multi-modal biometric identification system. The oppositional gray wolf optimization (OGWO) +LQ algorithm and multi-kernel support vector machine (MKSVM) technology were used to demonstrate the effectiveness of the methodology.

Jaswal and Poonia [41] proposed a multi-modal biometric method that uses palm and finger-knuckle photos to identify victims of physical abuse or kidnapping. Through the use of 2D2 LDA and the backtracking search technique, the study was able to increase recognition and verification performance by representing features using line ordinal pattern (LOP) encoding and non-decimated quaternion wavelet. The suggested strategy is far better considering overall performance.

Tharewal et al. [42] instead of depending on pre-trained models, try to create custom fusion deep-learning classification algorithms for every character. For example, palm-print picture identification accuracy is increased when CNN is combined with a Support Vector Machine (SVM) to learn finger veins. Using deep learning algorithms, the study investigates a wider range of identification features, including hand shapes, DNA, and signatures. Using a variety of multi-modal datasets and multi-level fusion processes, the suggested model shows encouraging results, with score-level fusion on 3D face and ear datasets.

Mohammed et al. [43] explore the potential of multi-biometric fusion for unique identification, putting forth the novel feature-level approach known as the Dis-Eigen algorithm. The framework leverages the fingerprints and faces of 20 persons, to improve identification accuracy by focusing on feature-level fusion.

Joseph et al. [44] built a multi-modal biometric system using the Convolutional Neural Network (CNN) and ORB (Oriented Fast and Rotated Brief) algorithm that is based on face and fingerprint identification. For two features, the study uses matching score-level fusion with a weighted sum rule. After a thorough analysis utilizing datasets from the UCI Repository of Machine Learning, the system produces encouraging results in person recognition.

Banati et al. [45] suggest a biometric framework based on score-level fusion, which combines fingerprint, palm print, and face biometric modalities. The final fusion score for identity verification is produced by the study by combining several biometric data to derive scores. The authentication procedure combines methods like Accelerated Robust Features (SURF) and Scale-Invariant Feature Transformation (SIFT). By using the fusion rules MIN, MAX, and SUM, a high authentication rate of 95.08% is attained, which is higher than the rates of SIFT and SURF separately.

Chang et al. [46] Using a scheme for format-preserving encryption, combine fuzzy commitments and fuzzy vaults to develop BIOFUSE, a strategy for multi-biometric fusion in cryptosystems. SBIOFUSE (S3) is the only one of the four approaches that is considered secure. On the virtual IITD-DB1 database, comparative evaluations with other multi-biometric cryptosystems show a better match rate with good recognition performance and improved security.

3. Discussion and Findings

The survey paper provides a comprehensive overview of multimodal biometric authentication systems using machine learning and deep learning techniques. The analyzed studies showcase a diverse range of modalities, fusion approaches, and algorithms employed for enhanced identification. Several key observations and discussions emerge from the literature survey. The efficiency of feature-level fusion in improving verification performance, the novel applications of non-traditional modalities including EEG signals and finger knuckle images, and the contributions of deep learning models to accuracy and efficiency are among the noteworthy discoveries. Security considerations highlight how biometric authentication is changing to meet modern problems, as evidenced by one study's proposal of a cryptosystem. Future studies should take into account the necessity for standardization and the variability in performance measurements. The literature survey highlights the dynamic nature of multimodal biometrics and its potential for reliable and secure identity solutions.

4. Conclusion

In conclusion, the survey provides a comprehensive overview of multimodal biometric authentication, showcasing the diverse modalities and fusion approaches used in various studies. The results highlight the potential of multimodal systems to improve efficiency, security, and accuracy—particularly when deep learning models are integrated and unusual attributes are explored. Nonetheless, problems with metric uniformity, practicality, and ethical issues still exist. Future research should focus on developing uniform evaluation measures, resolving ethical issues, and investigating hybrid models that include conventional and novel biometric features. To guarantee the broad and successful adoption of multimodal biometric authentication systems, research endeavors should also concentrate on improving security protocols, carrying out extensive deployment studies, and examining user experience elements.

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