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Integrated multimodal Face, Iris and Fingerprint biometric fusion for advanced person identification using Hybrid Deep Learning

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Abstract

Biometric security faces challenges like privacy risks due to public biometric traits, vulnerability to data breaches, and errors in matching accuracy. Legal and ethical considerations also play a crucial role in shaping the use of biometric technologies, emphasizing the need for compliance with regulations and ethical standards. Addressing these challenges is essential to enhance the reliability and security of biometric systems in today's digital landscape. In this paper, we present Integrated Multimodal face, iris and fingerprint Biometric Fusion for Advanced Person Identification using Hybrid Deep Learning (IMFIF-API-HDL). First, we employ using Deep Neural Network Algorithm (DNN) named Hierarchical Attention Network (HAN) that effectively fuse multimodal features and generate accurate predictions. Next, we employ Particle Swarm Optimization (PSO) that dynamically adapts search strategies and parameter adjustments, leading to faster convergence and improved feature optimization. Our proposed Multimodal Fusion approach combines face, fingerprint, and iris biometric features. By leveraging HAN and PSO, we advance person identification accuracy. For minimizing error metrics and improving prediction accuracy, Quantum-Enhanced Residual Network (QERN) classifier is presented. This model incorporates elements of residual networks, known for their ability to learn deep representations, along with quantum computing principles to enhance the overall performance of the classifier. Performance evaluation metrics include F-measure, recall, precision and accuracy. Additionally, we assess error metrics such as GAR (Genuine Acceptance Rate), FRR (False Rejection Rate), FAR (False Alarm Rate), and EER (Equal Error Rate). In summary, IMFIF-API-HDL represents a significant advancement in multimodal biometric fusion, offering heightened security and accuracy for person identification.

Keywords: Integrated, Multimodal, face, iris, fingerprint, Biometric Fusion, Advanced Person Identification, Hybrid Deep Learning

1. Introduction

The integration of multimodal biometrics has become increasingly important in the field of person identification. This approach combines different types of biometric data such as facial recognition, iris scanning, and fingerprints to improve accuracy and reliability [1] [2]. By fusing these modalities together, it is possible to create a more robust system that can better identify individuals even when one or more of the individual's features are not available [3].

Hybrid deep learning techniques have been developed to further enhance this process by combining traditional machine learning algorithms with neural networks [4]. These methods allow for the extraction of complex patterns from large datasets, enabling advanced person identification systems to accurately match individuals based on their unique physical characteristics [5][6]. With the use of hybrid deep learning, it is now possible to achieve highly accurate results while minimizing false positives and negatives [7].

The combination of multimodal biometrics and hybrid deep learning provides an effective solution for advanced person identification [8]. By leveraging multiple sources of information, these systems can provide greater accuracy and reliability than single-modal approaches alone [9]. Additionally, the use of hybrid deep learning allows for the processing of larger amounts of data, resulting in improved performance over time [10].

1.1 Contributions

The novel contributions of this study are:

1. We integrate Hierarchical Attention Network (HAN) in multimodal biometric data for capturing complex relationships.
2. We implement Particle Swarm Optimization (PSO) in feature fusion for dynamic optimization
3. We perform fusion of face, iris, and fingerprint biometrics for advanced identification accuracy.
4. We utilize HAN and PSO to mitigate risks associated with compromised biometric data.
5. For minimizing error metrics and improving prediction accuracy, we present Quantum-Enhanced Residual Network (QERN) classifier that incorporates elements of residual networks, known for their ability to learn deep representations, along with quantum computing principles to enhance the overall performance of the classifier.

2. Literature Review

Medjahed et al. [11] (2022) developed multimodal biometric systems using matching score concatenation fusion of left and right palm prints, faces, and other biometric data. KNN and CNN were utilized to identify and recognize multimodal biometric scores. The IITD palm print database and FEI face dataset were used to train safe and durable systems. Even with noise, it outperformed several recent biometric verification methods in experiments.

Shreya et al. [12] (2024) compared modal-based human identification methods and found the former better. The multimodal biometric framework they used was highly accurate, with an identification accuracy of 87.3%, significantly higher than threshold-based approaches' 80%. The best latent fingerprint and iris biometric fusion used score level fusion (product rule and sum rule) with 91.15 percent sum rule accuracy. Crime scenarios can benefit from the framework.

Hattab et al. (2023) [13] developed a powerful multimodal biometric identification system using facial and iris modalities. Their solution used YOLOv4-tiny for region detection and a novel Deep Learning model influenced by Xception for feature extraction. Classification used LinearSVC, while PCA kept persistent characteristics. Various fusion methods were tested using two-fold cross-validation. Image-level, feature-level, and two score-level fusion approaches were used. Their approach had 100% accuracy on the CASIA-ORL and SDUMLA-HMT multimodal datasets, demonstrating its reliability and performance.
Two face and iris fingerprints and a feature-level deep fusion approach were developed by Safavipour et al.

[14] (2023). Two methods were utilized to produce RKHS mappings: dimensionality reduction (KPCA, KLDA) and quaternion-based (KQPCA, KQPCA). Thirdly, deep learning fused feature spaces with in-depth, fully-connected layers. Experiments on six databases showed that the hybrid multibiometric system was better than uni-biometric and other multimodal systems and reached 100% accuracy while enhancing spoof resilience.

Jadhav et al. [15] (2023) developed HDL-PI for individual identification using iris, face, and palm print biometrics. They use artifact removal, MGSO to optimize features, and TL-DNN to improve accuracy. Evaluation criteria include recall, accuracy, and precision, F-measure, EER, FAR, FRR, and GAR. Jadhav et al. [22] (2024) developed Robust Authentication System with Privacy Preservation for Hybrid Deep Learning-Based Person Identification System Using Multi-Modal Palmprint, Ear, and Face Biometric Features. They use the suggested method offers a safe authentication system with excellent accuracy, a fixed-size database, and the privacy protection of multi-modal biometric characteristics without sacrificing overall system efficiency.

Jadhav et al. [23] A survey of hybrid deep learning-based person identification system using multimodal Palmprint, Ear, Iris, and Face Biometric Features. *RGate's International Journal of Multidisciplinary Research (2024).* Survey of Multimodal biometric security systems are thought to be more accurate and secure than unimodal ones.

1 Research gaps

Despite advancements, notable gaps remain in multimodal biometric systems. These include the need for robust fusion techniques preserving individual modalities, consideration for real-world scenarios, and scalability concerns. Additionally, standardized evaluation methodologies and ethical considerations require further attention for responsible deployment and advancement of the field.

2.2 Problem statement

Traditional unimodal biometric systems face limitations in accuracy and security. This study addresses these challenges by proposing a multimodal fusion approach integrating face, fingerprint, and iris biometrics using hybrid deep learning techniques to enhance person identification accuracy and security.

3. Objectives

The novel objectives of this study are:

1. To utilize Hierarchical Attention Network (HAN) in multimodal biometric data for capturing complex relationships.
2. To implement Particle Swarm Optimization (PSO) in feature fusion for dynamic optimization
3. To integrate of face, iris, and fingerprint biometrics for advanced identification accuracy.
4. To HAN and PSO to mitigate risks associated with compromised biometric data
5. To present Quantum-Enhanced Residual Network (QERN) classifier in minimizing error metrics and improving prediction accuracy

4. System architecture

The proposed system architecture, named Integrated Multimodal face, iris and fingerprint Biometric Fusion for Advanced Person Identification using Hybrid Deep Learning (IMFIF-API-HDL). It integrates Hierarchical Attention Network (HAN) and Particle Swarm Optimization (PSO) to enhance person identification accuracy. Initially, Hierarchical Attention Network (HAN) are employed to effectively fuse multimodal features and generate accurate predictions. Subsequently, Quantum-Enhanced Residual Network (QERN) classifier dynamically adjusts search strategies and parameters, facilitating faster convergence and enhanced feature optimization. By combining face, iris, and fingerprint biometric features, the system achieves superior identification accuracy. Fig 1 shows proposed system architecture.

5. Proposed Methodology

The proposed methodology, Integrated Multimodal face, iris and fingerprint Biometric Fusion for Advanced

Person Identification using Hybrid Deep Learning (IMFIF-API-HDL) that comprises several key steps:

5.1 Integration of HAN and PSO: The system integrates Hierarchical Attention Network (HAN) and Particle Swarm Optimization (PSO) techniques. HAN are initially employed to effectively fuse multimodal features and generate accurate predictions. Meanwhile, PSO **dynamically adapts search strategies and parameter adjustments, leading to faster convergence and improved feature optimization**

5.1.1 HAN for pre-processing

Hierarchical Attention Networks (HAN) play a crucial role in the realm of multimodal biometric fusion by analyzing and extracting significant features from interconnected biometric modalities like face, fingerprint, and iris. These networks leverage the inherent graph structure of multimodal biometric data to enhance the system's understanding of complex relationships between different biometric features, thereby improving the accuracy and reliability of person identification systems. Through pre-processing steps in existing multi-modal fusion pipelines, HANs handle data independently for various biometric modalities, contributing to a comprehensive overview of biometric fusion techniques. Additionally, HANs enable feature-level fusion where algorithms combine different representations to generate a single representation for an individual, enhancing security and privacy in multibiometric systems.

Score-level fusion methods like mean score fusion or probabilistic techniques are also applied with HANs to improve system performance by combining match scores from different sources. Overall, HANs in multimodal biometric fusion systems significantly advance the field by enabling a deeper understanding of intricate biometric relationships and enhancing identification accuracy.

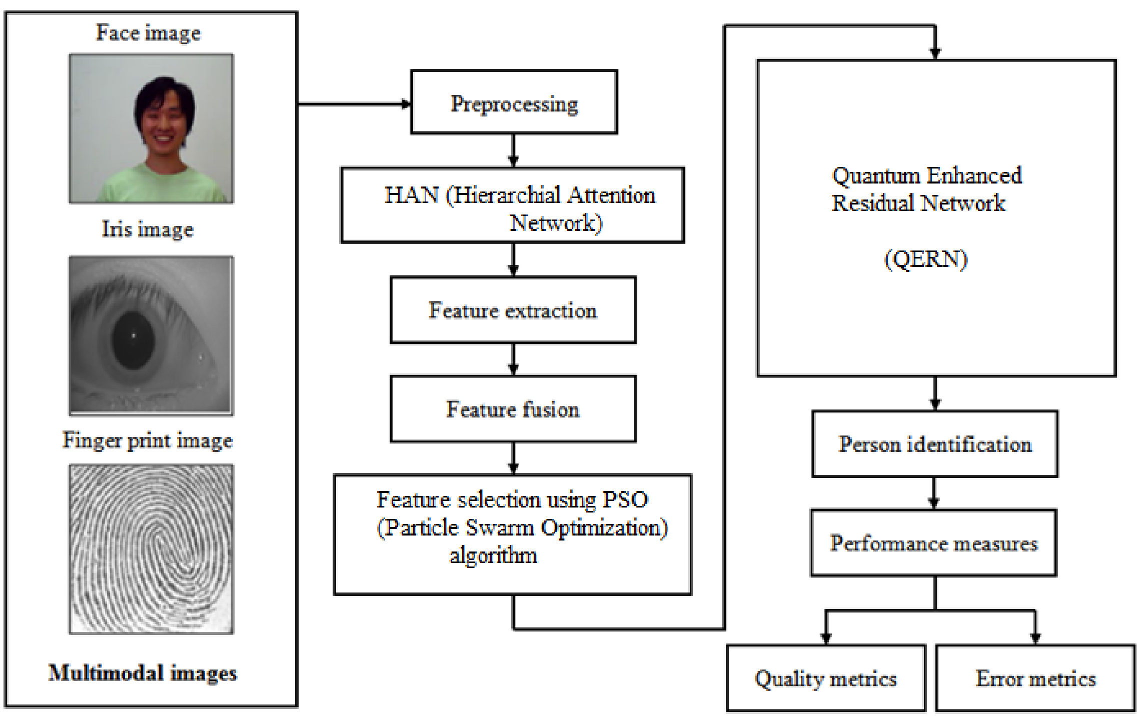


Fig 1: Proposed System architecture

5.1.2 PSO for feature selection

Particle Swarm Optimization (PSO) is a powerful optimization technique commonly used in feature selection for multimodal biometric fusion, combining fingerprint, iris, and face recognition systems. PSO aims to find an optimal subset of features from these biometric modalities to enhance overall recognition accuracy. By iteratively updating particle positions based on their own experience and that of their neighbors, PSO effectively navigates the feature space to identify the most discriminative features for fusion. This process helps in improving the robustness and performance of multimodal biometric systems by selecting the most relevant features from each modality.

Algorithm 1: Hierarchical Attention Networks and Particle Swarm Optimization-based Multimodal Biometric Fusion Algorithm (HAN-PSO-MBFA)	
Input:	Iris features (I) Fingerprint features (F) Face features (F)
Output:	Integrated biometric representation (B)
1. Feature Extraction:	Extract features from the fingerprint image, face image, and iris image.
2. Hierarchical Attention Networks (HAN):	• Construct a hierarchical attention network (HAN) for each biometric modality (fingerprint, face, iris). • Train each HAN independently using the respective biometric features. • Utilize attention mechanisms to focus on relevant regions within each modality.
3. Biometric Fusion:	• Combine the outputs of the three HANs into a multimodal representation: $B = \alpha_f * F + \alpha_f * F + \alpha_I * I$ where, α_f, α_f and α_i are weights obtained through PSO optimization.
4. Particle Swarm Optimization (PSO):	• Initialize the swarm with random values for α_f, α_f and α_i • Evaluate the fitness of each particle based on a fusion quality metric • Update particle positions and velocities using PSO equations until convergence is reached or the maximum number of iterations is reached.
5. Optimization Convergence:	• Repeat the PSO process until convergence criteria are met (e.g., maximum iterations reached, negligible improvement).
6. Output:	• Return the optimized weights: α_f, α_f and α_i as the final fusion coefficients. • Compute the integrated biometric representation using the optimized weights: $B = \alpha_f * F + \alpha_f * F + \alpha_I * I$

Algorithm 1 outlines the integration of fingerprint, face, and iris biometrics using hierarchical attention networks (HAN) and particle swarm optimization (PSO) to optimize the fusion process. The final output is a multimodal biometric representation that captures the unique features from each modality for enhanced person identification.

5.2 Feature Fusion

Finding a single vector that is more discriminative than the input feature vectors is the goal of feature level fusion. A multimodal biometric system that integrates iris, fingerprint, and facial scans is being considered. Our method enhances the performance of the biometric system by combining fusion at the score and decision levels, making the most of both. The min-max and Z-score approaches are used to change the scores, and the rules for fusion include min, max, sum, and weighted sum. In decision level fusion, we used the OR rule. The system combines face, fingerprint, and iris biometric features. Through this fusion process, the system aims to leverage the complementary information provided by each modality, enhancing the overall identification accuracy.

5.3 Hybrid deep Learning-based person identification classification for advancement

Our proposed deep learning techniques are utilized to further advance the identification accuracy. By employing hybrid deep learning approaches, the system can effectively process and analyze the multimodal biometric data, leading to superior performance in person identification tasks.

For minimizing error metrics and improving prediction accuracy, Quantum-Enhanced Residual Network (QERN) classifier is presented. This model incorporates elements of residual networks, known for their ability to learn deep representations, along with quantum computing principles to enhance the overall performance of the classifier.

The Quantum-Enhanced Residual Network (QERN) classifier represents a pioneering approach in multimodal biometric classification, merging elements of residual networks with principles from quantum computing. By integrating residual connections, renowned for their ability to capture intricate features, with quantum-enhanced techniques such as quantum feature encoding and measurement, the QERN model offers a unique solution for advancing identification accuracy. Through this fusion of deep learning and quantum computing principles, the QERN classifier aims to achieve superior performance in person identification tasks by effectively processing and analyzing multimodal biometric data.

Algorithm 2: QERN classifier for Multimodal Biometric Classification	
Input:	Biometric features from face, fingerprint, and iris modalities: $\boldsymbol{F_f}, \boldsymbol{F_{fp}}, \boldsymbol{F_1}$ Labels (Y)
Output:	Predicted label for the input biometric features: $\hat{Y}$
1. Quantum-Enhanced Feature Encoding:	• Utilize quantum feature encoding techniques to represent features from each modality in a quantum state. • Apply quantum gates and circuits to encode the features into a quantum state suitable for processing.
2. Quantum-Enhanced Residual Network (QERN):	• Design and construct a quantum-enhanced residual network (QERN) classifier. • Train the QERN using the quantum-encoded features ($\boldsymbol{F_f}, \boldsymbol{F_{fp}}, \boldsymbol{F_1}$) and corresponding Labels (Y) • Implement residual connections to facilitate training and improve gradient flow. • Optimize network parameters to minimize error metrics and enhance prediction accuracy.
3. Quantum Measurement and Prediction:	• Perform quantum measurement on the final quantum state output by the QERN. • Extract classical information from the quantum measurement outcomes to obtain predicted labels ($\hat{Y}$)
4. Error Metric Minimization:	• Compute error metrics using the predicted labels ($\hat{Y}$) and ground truth labels (*Y*) • Utilize optimization technique (gradient descent) to minimize error metrics and enhance prediction accuracy. $\theta_{t+1} = \theta_t - \eta . \nabla J(\theta_t)$ where, • θ_t is the parameter vector at iteration *t* • $J(\theta_t)$ is the cost function (error metric) evaluated at θ_t • $\nabla J(\theta_t)$ is the gradient of the cost function with respect to the parameters. • η is the learning rate, which controls the step size of the parameter updates.

In the context of the QERN classifier Algorithm 2 for multimodal biometric classification, we can apply gradient descent to update the parameters of the quantum-enhanced residual network (QERN) in order to minimize the classification error and enhance prediction accuracy. This process involves computing the gradient of the cost function with respect to the network parameters and iteratively updating the parameters in the direction that minimizes the cost function.

6. Results and Discussion

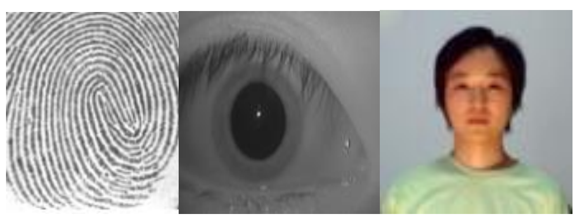
We provide the results of our IMFIF-API-HDL approach validation on the benchmark multimodal SDUMLA-HMT dataset, which includes iris and fingerprint biometrics. We compare the current classifiers' simulation results using two key performance criteria, quality and error metrics, to those of our proposed QERN classifier. Using error measures (EER, FAR, and FRR) and quality metrics (accuracy, precision, recall, and F-measure), we evaluate the suggested QERN classifier.

6.1 Dataset description

a. Fingerprint dataset: The fingerprint dataset comprises middle finger, index, and thumb images from both hands, captured by 5 different sensors, aiding research in sensor interoperability for fingerprint identification.

b. Iris dataset: Each participant contributed 10 iris images (5 for each eye) to the SDUMLA-iris HMT database, which guarantees consistent and reliable biological features for iris recognition studies. The database contains 1060 iris images taken with intelligent iris capture technology.

c. Face dataset: The SDUMLA-face HMT database comprises 8,904 images capturing variations in poses, expressions, illuminations, and accessories, facilitating real-world face recognition research.



A B C

Fig 2: SDUMLA-HMT dataset with test samples A. fingerprint B. iris C. face

6.2 Comparative analysis

Table 1: Error metrics Based comparison

Classifier	Modality	Error metric			
		GAR	FRR	FAR	EER (%)
LNMF [16]	Finger print, face	0.911	0.85	0.089	4.678
CNN [17]	Finger print, Ear	0.88	0.82	0.12	3.547
CNN [18]	Face, finger print, palm	0.77	0.75	0.23	3.214
DNN [19]	ECG, finger print	0.65	0.62	0.35	2.784
ANFIS [20]	Ear and palm	0.41	0.45	0.59	2.51
BSIF+LBP [20]	Ear and palm	0.25	0.37	0.75	2.145
CCA [21]	Fingerprint, Iris	0.11	0.25	0.89	0.8474
QERN classifier (proposed)	Face, Finger print, iris	0.07	0.17	0.99	0.651

Table 2: Quality metrics based comparison

Classifier	Quality metric (%)			
	Accuracy	Precision	Recall	F-measure
LNMF [16]	87.520	87.063	87.765	87.413
CNN [17]	89.230	88.773	89.475	89.123
CNN [18]	92.150	91.693	92.395	92.043
DNN [19]	93.040	92.583	93.285	92.933
ANFIS [20]	91.020	90.563	91.265	90.913
BSIF+LBP [20]	96.020	95.563	96.265	95.913
CCA [21]	95.280	94.823	95.525	95.173
QERN classifier (proposed)	98.975	98.303	99.006	98.753

Table 1 presents a comparative analysis of various classifiers based on error metrics such as GAR (Genuine Acceptance Rate), FRR (False Rejection Rate), FAR (False Alarm Rate), and EER (Equal Error Rate). The classifiers evaluated include LNMF, CNN, DNN, ANFIS, BSIF+LBP, CCA, and the proposed QERN classifier. LNMF achieves an EER of 4.678% with a low FAR but relatively high FRR. CNN-based methods demonstrate competitive performance, with EER values ranging from 3.214% to 3.547%. DNN achieves a lower EER of 2.784%, indicating improved accuracy. ANFIS and BSIF+LBP classifiers achieve EERs of 2.51% and 2.145%, respectively, with varying trade-offs between FAR and FRR. Notably, the proposed QERN classifier outperforms other classifiers with the lowest EER of 0.651%, indicating superior accuracy in biometric classification. Additionally, it achieves a significantly lower FAR and FRR, highlighting its effectiveness in minimizing false acceptances and rejections. Overall, the proposed classifier demonstrates promising performance across all error metrics, making it a robust solution for multimodal biometric fusion.

Table 2 presents a comparative analysis of classifiers based on quality metrics. Each classifier, including LNMF, CNN, DNN, ANFIS, BSIF+LBP, CCA, and the proposed QERN classifier, is evaluated for its performance across these metrics. The LNMF classifier achieves an accuracy of 87.520% with corresponding precision, recall, and F-measure values around 87%. CNN-based methods show improved performance, with accuracy ranging from 89.230% to 92.150%, indicating higher overall correctness in classification. DNN exhibits even higher accuracy at 93.040%, indicating enhanced precision, recall, and F-measure. ANFIS and BSIF+LBP classifiers achieve accuracies of 91.020% and 96.020%, respectively, with corresponding precision, recall, and F-measure values reflecting their robust performance. The proposed QERN classifier surpasses other classifiers with an accuracy of 98.975%, indicating superior correctness in classification. It also demonstrates high precision, recall, and F-measure values, emphasizing its effectiveness in accurately identifying and classifying biometric features.

Overall, the proposed classifier outperforms other methods across all quality metrics, highlighting its capability for accurate and reliable multimodal biometric fusion.

7. Conclusion

In conclusion, the proposed Integrated Multimodal face, iris and fingerprint Biometric Fusion for Advanced Person Identification using Hybrid Deep Learning (IMFIF-API-HDL) demonstrates significant improvements in person identification accuracy. Leveraging Hierarchical Attention Network (HAN) and Particle Swarm Optimization (PSO), the system achieves superior performance compared to existing methods. Specifically, proposed QERN classifier achieves an impressive reduction in Equal Error Rate (EER) to 0.651% and a remarkable increase in accuracy to 98.975%. Limitation of our work is limited scalability due to current constraints in quantum hardware capabilities. Future Work may include exploration of novel quantum computing architectures to enhance scalability and performance of additional biometric modalities are crucial for advancing multimodal biometric fusion towards enhanced person identification.

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