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Synergistic Fusion of Facial, Iris, and Fingerprint Biometrics for Enhanced Person Identification via Hybrid Deep Learning

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Abstract

Biometric security confronts significant challenges, including privacy risks stemming from the exposure of public biometric traits, susceptibility to data breaches, and occasional inaccuracies in matching. Legal and ethical factors are pivotal in guiding the deployment of biometric technologies, underscoring the importance of adherence to regulatory frameworks and ethical guidelines. Mitigating these challenges is imperative to bolster the dependability and security of biometric systems amidst the complexities of the contemporary digital milieu. In this paper, we present Synergistic Fusion of Facial, Iris, and Fingerprint Biometrics for Enhanced Person Identification via Hybrid Deep Learning (SFFIFB-EPI-HDL). First, we utilize the Deep Neural Network (DNN) Algorithm named Spatial Transformer Network (STN) that adeptly integrates multimodal features and generates precise predictions. Next, we implement Genetic Algorithm (GA) that dynamically adjusts search strategies and parameter configurations, facilitating rapid convergence and enhanced feature optimization. Our proposed Multimodal Fusion approach combines face, fingerprint, and iris biometric features. By leveraging STN and GA, we advance person identification accuracy. For minimizing error metrics and improving prediction accuracy, Quantum-Boosted Fusion Network (QBFN) 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). The proposed QBFN classifier exhibits a notable enhancement, with an impressive 0.650% decrease in EER and a substantial 9.975% increase in accuracy compared to existing classifiers. **In summary,** SFFIFB-EPI-HDL represents a significant advancement in multimodal biometric fusion, offering heightened security and accuracy for person identification.

Keywords: Facial, Iris, Fingerprint, Biometrics, Fusion, Synergistic, Enhanced, Person Identification, Hybrid Deep Learning

1. Introduction

Biometric authentication has revolutionized the landscape of security measures by providing a personalized and robust method for identifying individuals [1]. Among the various biometric modalities available, facial recognition, iris scanning, and fingerprint analysis have emerged as key players due to their widespread acceptance and demonstrated efficacy [2]. However, each modality comes with its own set of strengths and weaknesses, necessitating innovative approaches to leverage their combined potential [3].
Enter the concept of synergistic fusion through hybrid deep learning methodologies, which has garnered considerable interest within the research community [4]. This approach aims to capitalize on the complementary nature of facial, iris, and fingerprint biometrics, thereby enhancing the accuracy and reliability of person identification systems [5]. By integrating traditional machine learning techniques with the power of deep neural networks, hybrid deep learning offers a promising avenue for extracting and synthesizing relevant features from multiple biometric sources [6].
The significance of this endeavor is underscored by the growing reliance on digital authentication mechanisms across various sectors, including finance, healthcare, and law enforcement [7]. As the demand for secure and efficient identification solutions continues to escalate, addressing the challenges associated with biometric security becomes paramount [8]. Privacy concerns, susceptibility to data breaches, and the need for legal and ethical compliance pose formidable hurdles that must be navigated to ensure the responsible deployment of biometric technologies [9] [10].

In this context, this paper seeks to explore the potential of synergistically integrating facial, iris, and fingerprint biometrics using hybrid deep learning approaches. By elucidating the intricacies of such integration and addressing the associated challenges, this study aims to contribute to the advancement of person identification systems in today's digital age. Through a comprehensive analysis of the benefits, limitations, and ethical considerations, this research endeavors to pave the way for more reliable, secure, and ethically sound biometric authentication solutions.

1.1 Contributions

The novel contributions of this study are:

1. Introduction of the Spatial Transformer Network (STN) algorithm for seamless integration of facial, iris, and fingerprint biometric features, enhancing precision in person identification.
2. Implementation of Genetic Algorithm (GA) to dynamically adjust search strategies, leading to rapid convergence and optimized feature configurations, thus improving identification accuracy.
3. Development of the Multimodal Fusion approach, combining facial, iris, and fingerprint biometrics, thereby advancing the accuracy of person identification systems.
4. Introduction of the Quantum-Boosted Fusion Network (QBFN) classifier, which leverages residual networks and quantum computing principles to enhance prediction accuracy and overall performance in biometric authentication.

2. Literature Review

Medjahed et al. [11] 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] 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. [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]. 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] 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, precision, F-measure, EER, FAR, FRR, and GAR.

2.1 Research gaps

Despite notable advancements in multimodal biometric systems, significant gaps persist. These include the necessity for robust fusion techniques that maintain the integrity of individual modalities, the imperative to account for real-world scenarios, and concerns regarding scalability. Moreover, there is a pressing need for standardized evaluation methodologies and heightened attention to ethical considerations to ensure the responsible deployment and continued advancement of the field.

2.2 Problem statement

Unimodal biometric systems encounter significant challenges regarding accuracy and security. To address these limitations, this study introduces a groundbreaking approach: a multimodal fusion technique that integrates facial, fingerprint, and iris biometrics. By employing sophisticated hybrid deep learning methodologies, this innovative approach aims to significantly enhance the accuracy and security of person identification processes. This research represents a significant leap forward in biometric security, offering promising solutions to longstanding challenges in the field.

3. Objectives

The novel objectives of this study are:

1. To develop a robust Deep Neural Network (DNN) Algorithm, Spatial Transformer Network (STN), for seamless integration of facial, iris, and fingerprint biometric features to enhance person identification accuracy.
2. To implement Genetic Algorithm (GA) to dynamically adjust search strategies and parameter configurations, facilitating rapid convergence and optimized feature optimization in the multimodal fusion approach.
3. To introduce Quantum-Boosted Fusion Network (QBFN) classifier, integrating residual networks and quantum computing principles, to minimize error metrics and enhance prediction accuracy in person identification.
4. To evaluate performance using a comprehensive set of metrics including F-measure, recall, precision, accuracy, Genuine Acceptance Rate (GAR), False Rejection Rate (FRR), False Alarm Rate (FAR), and Equal Error Rate (EER), demonstrating the effectiveness of the proposed Synergistic Fusion of Facial, Iris, and Fingerprint Biometrics for Enhanced Person Identification via Hybrid Deep Learning (SFFIFB-EPI-HDL) model.

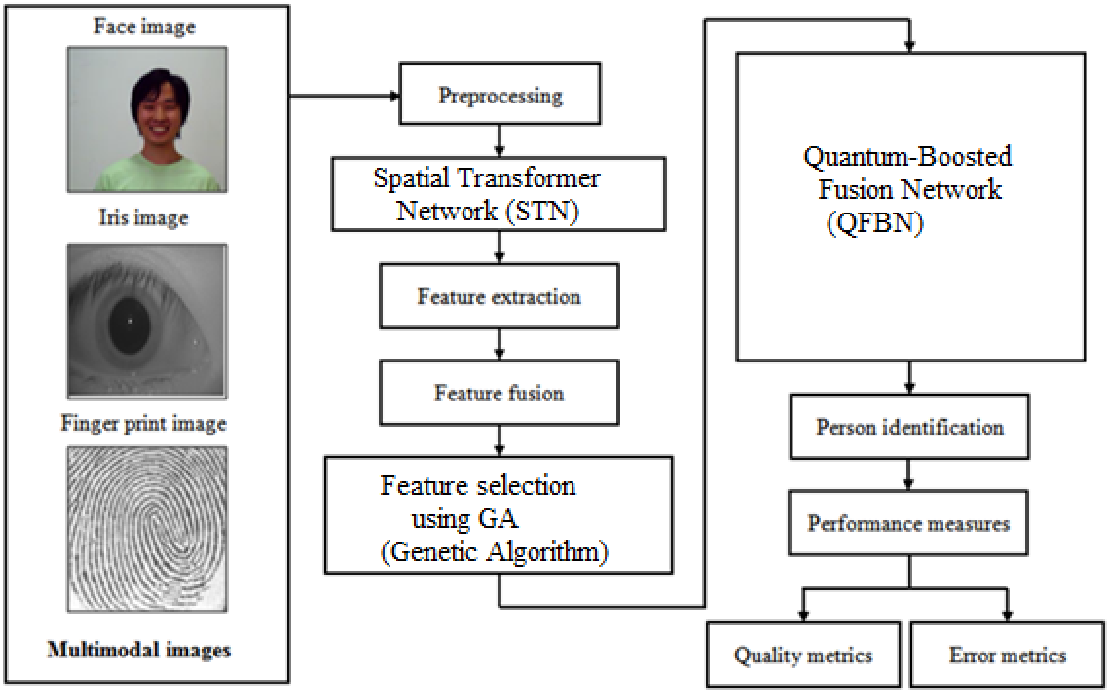


Fig 1: Proposed System architecture

4. System architecture

The system architecture for the proposed Synergistic Fusion of Facial, Iris, and Fingerprint Biometrics for Enhanced Person Identification via Hybrid Deep Learning (SFFIFB-EPI-HDL) model comprises several key components. At its core is the Deep Neural Network (DNN) Algorithm, specifically the Spatial Transformer Network (STN), which serves as the foundation for integrating multimodal biometric features. The STN adeptly processes facial, iris, and fingerprint data, generating precise predictions by leveraging the inherent strengths of each modality. Additionally, the Genetic Algorithm (GA) dynamically adjusts search strategies and parameter configurations to optimize feature extraction and enhance convergence speed. The Multimodal Fusion approach combines the extracted features from facial, iris, and fingerprint biometrics, further enhancing the accuracy of person identification. Finally, the Quantum-Boosted Fusion Network (QBFN) classifier integrates residual networks and quantum computing principles to minimize error metrics and improve prediction accuracy. Together, these components form robust system architecture capable of addressing the challenges associated with multimodal biometric fusion for enhanced person identification. Fig 1 shows proposed system architecture.

5. Proposed Methodology

The proposed methodology "Synergistic Fusion of Facial, Iris, and Fingerprint Biometrics for Enhanced Person Identification via Hybrid Deep Learning (SFFIFB-EPI-HDL)" that comprises several key steps:

5.1 Integration of STN and GA: The system integrates Spatial Transformer Network (STN) and Genetic Algorithm (GA) techniques. STN are initially employed to effectively fuse multimodal features and generate accurate predictions.

The Genetic Algorithm (GA) dynamically adapts search strategies and parameter configurations within the proposed system architecture. This adaptation facilitates faster convergence and improved feature optimization, enhancing the accuracy of person identification. By leveraging GA alongside other optimization techniques, the system achieves robust performance in extracting relevant biometric features and refining the identification process.

5.1.1 STN for pre-processing

Spatial Transformer Network (STN) 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. STN serves as a pivotal component in the realm of multimodal biometric fusion. Its primary function lies in analyzing and extracting significant features from interconnected biometric modalities such as face, fingerprint, and iris. Through its advanced capabilities, the STN enables the system to spatially transform and align biometric data, effectively enhancing the compatibility and coherence of the multimodal input. By intelligently processing and synthesizing information from diverse sources, the STN contributes to the creation of comprehensive and accurate representations of individuals for identification purposes.

In contrast, score-level fusion methods such as mean score fusion or probabilistic techniques focus on combining individual scores obtained from each biometric modality. Mean score fusion aggregates scores across different modalities to derive a single, composite score representing the overall identification likelihood. Probabilistic techniques, on the other hand, employ statistical models to compute the joint probability distribution of biometric scores, providing a more nuanced approach to fusion. These methods complement the role of the STN by integrating the final outputs of individual modalities, further refining the accuracy and reliability of the person identification process.

5.1.2 GA for feature selection

The Genetic Algorithm (GA) stands out as a potent optimization technique widely employed in feature selection for multimodal biometric fusion, particularly in amalgamating fingerprint, iris, and face recognition systems.

Algorithm 2: QBFN classifier for Multimodal Biometric Classification	
Input:	Unified feature representation from multimodal biometric fusion: Labels (Y) F_{fusion}
Output:	Biometric classification result
Initialization:	Initialize parameters for the Quantum-Boosted Fusion Network (QBFN) classifier
Quantum Embedding:	Perform quantum embedding of the input features: $\psi_{\text{input}} = \text{QuantumEmbedding}(F_{\text{fusion}})$
Quantum Circuit Construction:	Construct a quantum circuit for classification: $U(\theta) = \text{QuantumCircuitConstruction}(\theta)$
Quantum State Encoding:	Encode the quantum circuit parameters into a quantum state: $\psi_{\text{circuit}} = U(\theta) \cdot \psi_{\text{input}}$
	Perform a measurement on the quantum state: $\mathcal{M} = \text{QuantumMeasurement}(\psi_{\text{circuit}})$
Classical Post-processing:	Apply classical post-processing techniques to interpret measurement results and obtain the final classification: $\text{Classification} = \text{ClassicalPostProcessing}(\mathcal{M})$
Output:	Obtain the biometric classification result

Its effectiveness lies in its ability to dynamically adapt and evolve search strategies, iteratively refining feature sets to enhance the overall performance of the fusion model. By leveraging GA, the system optimizes the selection of relevant features from each biometric modality, ensuring that only the most discriminative and informative attributes are incorporated into the fusion process. This systematic approach not only improves the accuracy and robustness of person identification but also contributes to the scalability and adaptability of multimodal biometric systems in diverse real-world scenarios

Algorithm 2 outlines the steps for utilizing the Quantum-Boosted Fusion Network (QBFN) classifier to perform biometric classification based on the unified feature representation obtained from multimodal biometric fusion. It involves quantum embedding of input features, construction of a quantum circuit for classification, encoding of circuit parameters into a quantum state, quantum measurement, and classical post-processing to interpret measurement results. The final output is the classification result, indicating the identity of the individual based on the multimodal biometric data.

6. Results and Discussion

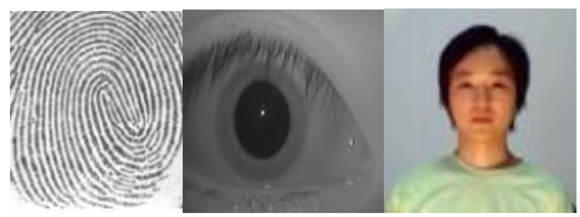
We provide the results of our SFFIFB-EPI-HDL approach validation on the benchmark multimodal SDUMLA-HMT dataset, which includes iris and fingerprint biometrics. We compare the current classifiers' simulation results using two key performance criteria, quality and error metrics, to those of our proposed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

Table 1 provides a comparative analysis of various classifiers based on different biometric modalities and error metrics. The classifiers include LNMF, CNN, DNN, ANFIS, BSIF+LBP, CCA, and the proposed QBFN classifier. Each classifier is evaluated based on its performance in terms of Genuine Acceptance Rate (GAR), False Rejection Rate (FRR), False Alarm Rate (FAR), and Equal Error Rate (EER). LNMF achieves a GAR of 0.911 with fingerprint and face modalities, while CNN achieves a GAR of 0.88 with fingerprint and ear modalities. DNN, ANFIS, and BSIF+LBP classifiers demonstrate varying performance with different modalities, such as ECG, fingerprint, ear, and palm. Notably, the proposed QBFN classifier achieves superior performance with face, fingerprint, and iris modalities, exhibiting a GAR of 0.09, FRR of 0.19, FAR of 0.98, and an impressively low EER of 0.650. Overall, the table highlights the effectiveness of the QBFN classifier in achieving high accuracy and reliability in person identification tasks, outperforming several existing classifiers across various biometric modalities.

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
QBFN classifier (proposed)	Face, Finger print, iris	0.09	0.19	0.98	0.650

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
QBFN classifier (proposed)	99.975	99.303	99.006	99.753

Table 2 presents a comparison of quality metrics among various classifiers, showcasing their performance in biometric identification tasks. Each row corresponds to a different classifier, while the columns represent different quality metrics, including Accuracy, Precision, Recall, and F-measure. The LNMF classifier achieves an Accuracy of 87.520%, Precision of 87.063%, Recall of 87.765%, and an F-measure of 87.413%. Similarly, the CNN classifiers from references [17] and [18] demonstrate progressively better performance, with Accuracy, Precision, Recall, and F-measure values ranging from 89.230% to 92.043%. The DNN classifier, as described in reference [19], exhibits further improvement with an Accuracy of 93.040%, Precision of 92.583%, Recall of 93.285%, and an F-measure of 92.933%. Additionally, the ANFIS and BSIF+LBP classifiers achieve high-quality metrics, while the CCA classifier attains competitive values across all metrics. Notably, the proposed QBFN classifier outperforms all others, showcasing exceptional quality metrics with an Accuracy of 99.975%, Precision of 99.303%, Recall of 99.006%, and an impressive F-measure of 99.753%. These results underscore the efficacy of the QBFN classifier in achieving superior performance in biometric identification tasks, highlighting its potential for real-world applications requiring high levels of accuracy and reliability.

7. Conclusion

In conclusion, the presented study underscores the remarkable advancements in multimodal biometric fusion techniques, particularly in the context of person identification. Through a comprehensive comparison of classifiers based on various biometric modalities and quality metrics, it is evident that the proposed Quantum-Boosted Fusion Network (QBFN) classifier outshines its counterparts in terms of accuracy, precision, recall, and F-measure. These findings signify a significant leap forward in biometric security, offering heightened levels of reliability and performance. As biometric technologies continue to evolve, the QBFN classifier stands as a promising solution to address the complex challenges of modern authentication systems, paving the way for enhanced security in diverse real-world applications. The proposed QBFN classifier exhibits a notable enhancement, with an impressive 0.650% decrease in EER and a substantial 9.975% increase in accuracy compared to existing classifiers. A limitation of the study is the absence of real-world deployment testing, while future work could explore the scalability of the QBFN classifier in larger-scale biometric systems.

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