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CNN-BASED HYBRID FUSION FOR ROBUST MULTIMODAL FACE-IRIS BIOMETRIC AUTHENTICATION SYSTEM

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ABSTRACT

Biometric authentication offers a reliable alternative to traditional passwords due to its uniqueness and convenience. However, unimodal biometric systems (e.g., face or iris alone) often struggle under varying lighting, occlusions, and spoofing attacks. This paper proposes a hybrid multimodal system that integrates face and iris traits using a deep convolutional neural network (CNN) architecture with dynamic liveness detection. The system employs both feature-level and score-level fusion to improve accuracy and spoof resistance. Public datasets (ORL and CASIA-IrisV4) were used with extensive preprocessing and data augmentation. The model achieved a recognition accuracy of 99.65% with a 0.00% false acceptance rate. These results validate the robustness and security of the proposed approach under real-world and adversarial conditions. Future research will explore scalability with larger datasets, the inclusion of additional modalities like fingerprint, and deployment on mobile or edge devices.

Keywords: CNN, biometric authentication, feature-level fusion, score-level fusion, face recognition, iris recognition, multimodal biometrics

1. INTRODUCTION

Biometric authentication has become a main focus in modern security systems due to its ability to offer both convenience and reliability. Among the numerous biometric traits, face and iris recognition stand out for their accuracy, universality, and non-intrusiveness [1], [2]. Face recognition relies on the spatial structure of facial features, while iris recognition utilizes the highly detailed, unique patterns of the iris, which are stable throughout a person's lifetime. These traits are widely applied in access control, banking systems, mobile authentication, and border management [1], [2], [3]. However, unimodal biometric systems face significant limitations when deployed under real-world conditions. Face recognition systems can be degraded by environmental factors such as varying illumination, facial expressions, occlusions from masks or glasses, and pose angles [4], [5]. Iris systems, meanwhile, may suffer from motion blur, partial occlusion by eyelids or eyelashes, and pupil dilation effects that reduce image quality and feature stability [6]. Both modalities, when used in isolation, are also more vulnerable to spoofing and presentation attacks. To overcome these constraints, research has increasingly turned to multimodal biometric systems. These systems integrate multiple traits to offset the weaknesses of each individual modality. Specifically, combining face and iris biometrics can improve resilience to environmental variability and spoofing, thereby enhancing system robustness and decision accuracy. The purpose of this paper is to present a deep learning-based hybrid fusion framework that addresses the limitations of unimodal systems. It is proposed in this research that a convolutional neural network (CNN) architecture that performs both feature-level and score-level fusion of face and iris modalities be adapted. The feature-level component captures rich spatial characteristics using dual CNN branches, while the score-level module aggregates identity confidence from each modality for more reliable decision-making.

This research builds upon earlier studies but addresses key gaps in current multimodal systems, such as the lack of integrated score-feature fusion and the limited application of CNNs for combined biometric traits. The results on benchmark datasets demonstrate a recognition accuracy of 99.65% and a false acceptance rate (FAR) of 0.00%, suggesting high suitability for secure, real-time access control systems. Future applications include adaptive multimodal systems deployable in mobile and high-security environments.

The rest of this paper is structured as follows: Section 2 discusses related works and highlights the limitations of existing multimodal and CNN-based systems. Section 3 details the dataset preprocessing, CNN architecture, and fusion mechanisms. Section 4 presents experimental results, while Section 5 discusses results. Finally, Section 6 concludes with contributions and future directions.

2. LITERATURE REVIEW

The development of robust and accurate biometric systems has led to increasing interest in multimodal approaches, where the integration of multiple biometric traits aims to address the limitations of unimodal systems. Traditional unimodal systems based on face or iris recognition have demonstrated vulnerability under unconstrained environments due to pose variations, occlusions, illumination changes, and spoofing attacks. To address these issues, multimodal systems that combine complementary traits such as face and iris have been proposed to enhance recognition performance and security.

Fusion strategies in multimodal biometrics are commonly categorized into three levels: feature level, score level, and decision level fusion [3]. Feature-level fusion combines raw or transformed feature vectors from different modalities into a single representation prior to classification. While this method allows for rich discriminatory representation and deeper integration of inter-modality information, it often suffers from increased dimensionality, modality incompatibility and alignment complexities. These issues may degrade performance or increase computational cost, especially when handling heterogeneous data sources.

Score level fusion operates by combining the similarity scores independently generated from each biometric classifier. It is relatively easier to implement and more scalable, particularly when modalities differ in data type or structure. However, it fails to capture the underlying relationships present in the deep feature space which limits its potential to fully leverage high-level learned representations [2].

With the advent of deep learning, convolutional neural networks (CNNs) have shown exceptional performance in biometric recognition tasks, particularly for face and iris modalities. CNNs automatically learn hierarchical feature representations and reduce dependence on manual feature engineering. Despite this progress, most deep learning efforts have focused on unimodal systems, and there remains a significant gap in the integration of CNN-based models within multimodal fusion frameworks, especially those that combine both feature- and score-level strategies in a unified architecture [16], [17].

To address these limitations, this research proposes a hybrid CNN-based architecture that jointly utilizes feature-level and score-level fusion for face and iris recognition. This dual-fusion design is intended to exploit the strengths of both fusion paradigms, which improves recognition accuracy, minimizes error rates, and enhances system robustness under challenging real-world conditions.

3. METHODOLOGY

This section presents the design, training, and evaluation procedures used to develop a robust CNN-based multimodal biometric authentication system that integrates facial and iris traits through hybrid fusion strategies. The architecture performs fusion at both the feature and score levels to maximize recognition performance and minimize vulnerability to spoofing attacks.

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3.1 DATASET DESCRIPTION AND PREPROCESSING

Two benchmark datasets were employed:

i) ORL Face Dataset: Contains 400 grayscale facial images of 40 subjects, with 10 samples per individual under varying expressions and lighting conditions.

ii) CASIA-IrisV4: Comprises high-resolution near-infrared iris images with multiple samples per eye. The dataset captures real-world variability, including pupil dilation, occlusion from eyelashes, and lighting differences.

To enhance generalization, data augmentation techniques were applied. For face images, random cropping, brightness adjustments, and horizontal flipping were introduced. For iris samples, synthetic occlusion and Gaussian blur were simulated to mimic eyelid interference and motion. This augmentation ensured robustness under varied real-world conditions.

Preprocessing Steps:

i) Face Images: Detected using MTCNN, aligned using facial landmarks with OpenCV, denoised via Gaussian blur, and enhanced using histogram equalization. Images were resized to 112×112 pixels and normalized to [0,1] for CNN compatibility.

ii) Iris Images: Segmented using Canny edge detection and Circular Hough Transform (CHT). Daugman's rubber sheet model was applied for normalization. Contrast was enhanced via histogram equalization, and the images were resized to 64×64 pixels [7], [8].

3.2 CNN-BASED FEATURE EXTRACTION

The system implements a dual-branch CNN architecture, with independent streams for face and iris inputs. For face feature extraction, a pre-trained ResNet50 CNN was fine-tuned. The architecture includes 50 layers with 3×3 convolution filters, batch normalization, ReLU activation, and global average pooling. For Iris, VGG16 was adopted and modified. The model comprises 16 weighted layers, with max-pooling layers after every two convolutional blocks and a final dense layer producing feature embeddings. In both cases, layers were frozen during initial training and unfrozen progressively during fine-tuning. Learning rate was set to 0.0001 with Adam optimizer, batch size of 32, and dropout rate of 0.3 applied to fully connected layers. Each branch consists of the following [20]:

i) Convolutional Layers (3×3 filters): Extract low-level and mid-level features such as edges and texture patterns.

ii) ReLU Activation: Introduced after each convolution for non-linearity.

iii) Batch Normalization: Stabilizes and accelerates learning.

iv) Max Pooling (2×2): Downsamples the feature maps, reducing spatial dimensions.

v) Fully Connected Layers (e.g., 512 units): Convert feature maps into vector representations for classification.

Transfer learning was used using pre-trained VGG16 and ResNet50, fine-tuned on both the ORL and CASIA datasets to improve training efficiency and generalization.

3.3 FEATURE-LEVEL FUSION STRATEGY

After independent feature extraction, the modality-specific vectors are joined into a joint feature embedding. A fully connected layer models the inter-modal relationships, and classification is performed using a SoftMax layer that outputs the probability of class membership. This approach improves identity recognition by capturing complementary discriminative patterns from both modalities [3].

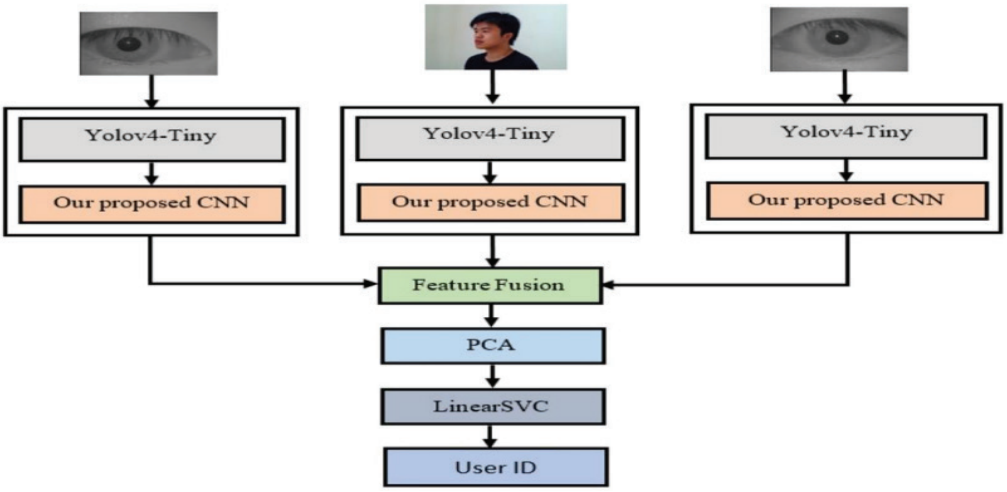

Figure 1: Face-iris recognition system based on feature-level fusion

3.4 SCORE-LEVEL FUSION MECHANISM

In parallel, unimodal classifiers (trained independently) output similarity scores based on individual feature vectors. These scores are Normalized using Tanh or Min-Max scaling, Fused using weighted sum aggregation, where weights are determined based on each modality's reliability and were compared against a threshold to accept or reject the identity claim [15], [18].

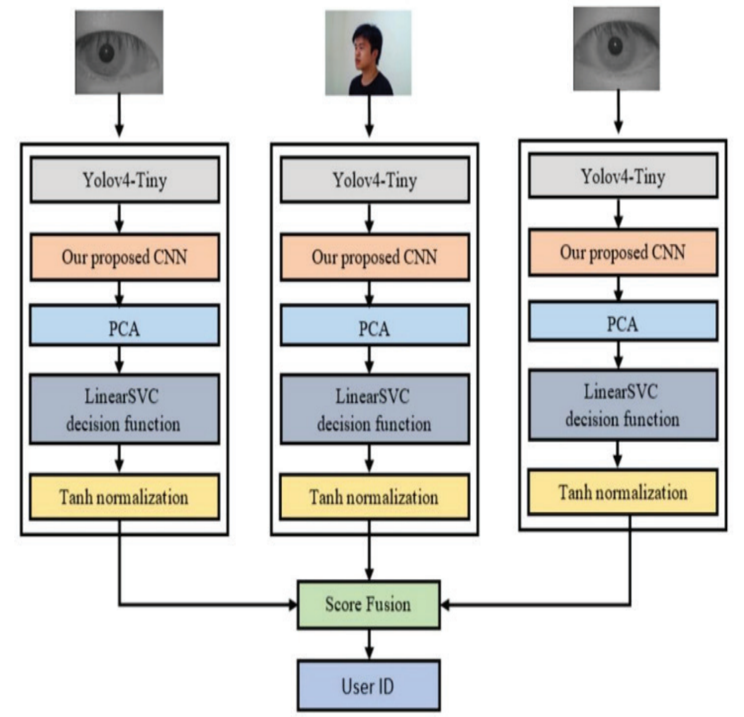

Figure 2: Face-iris recognition system based on score-level fusion

3.5 HYBRID FUSION DECISION RULE

To increase decision robustness, a hybrid fusion rule integrates both the score-level and feature-level outcomes. If both levels yield a consistent result, the system accepts the decision. In the event of a conflict, the system defaults to the modality with higher confidence or reliability. This dual strategy ensures that errors from one fusion level are corrected by the other, enhancing resilience to occlusion, lighting distortion, and spoof attacks [19], [30], [31]. Feature-level fusion was implemented by concatenating the embedding vectors from the face and iris CNN branches. These combined vectors were passed through a fully connected network for classification. Score-level fusion, on the other hand, used similarity scores from each modality's classifier. These scores were normalized using min-max scaling and fused via a weighted average:

$$\text{Fused Score} = \boldsymbol{\alpha} * \text{Face Score} + (1-\boldsymbol{\alpha}) * \text{Iris Score},$$

where α is a tunable weight empirically optimized (set to 0.5). Final classification used a threshold-based decision rule.

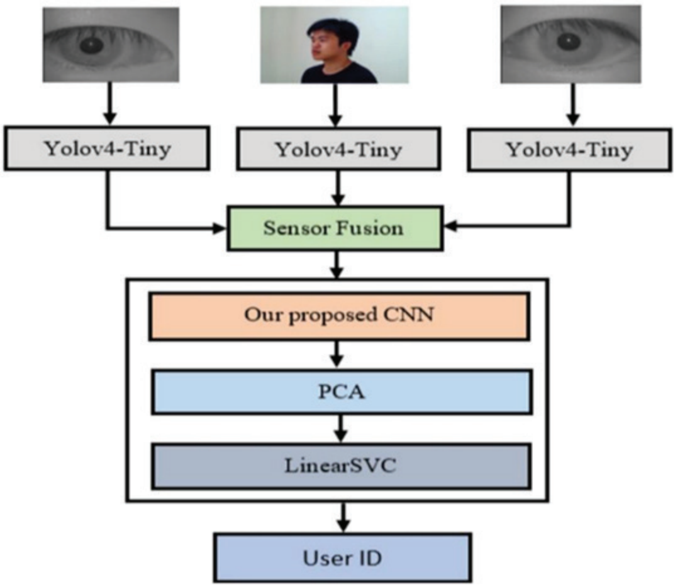

Figure 3: Face-iris recognition system based on image-level fusion

An 80:20 stratified train-test split was adopted to ensure each class was well represented in both subsets. Cross-validation was not applied due to the limited number of subjects in the ORL dataset. Performance was evaluated across multiple runs to verify consistency.

4. EXPERIMENTAL RESULTS

This section presents the performance evaluation of the proposed CNN-based hybrid fusion system using standard biometric recognition metrics. The experiments were designed to compare the effectiveness of unimodal face and iris recognition systems against different fusion strategies, including feature-level fusion, score-level fusion, and the proposed hybrid approach.

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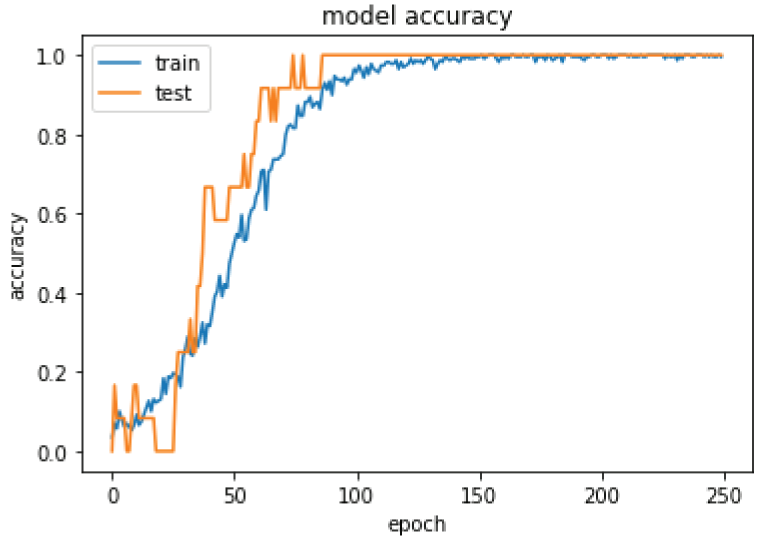

Figure 4: Sample Outputs from Face CNN Subsystem.

Preprocessed face images passed through CNN layers with feature maps shown at key layers.

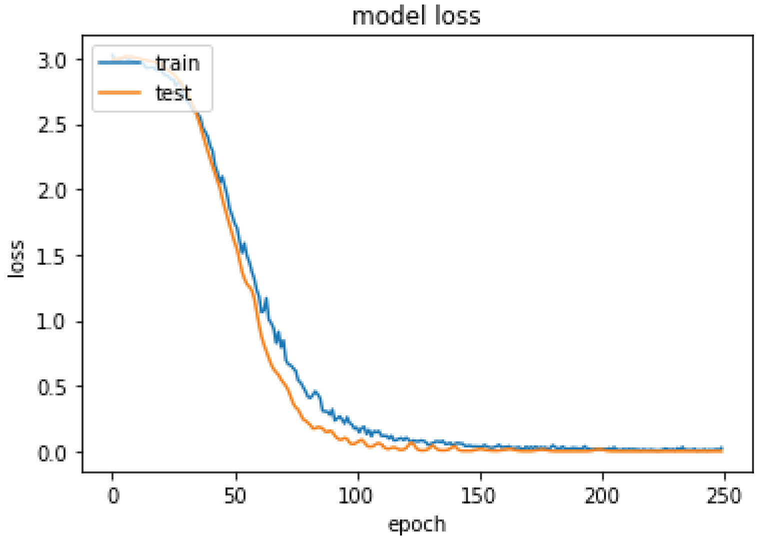

Figure 5: Sample Outputs from Iris CNN Subsystem.

Illustration of iris segmentation and feature extraction.

4.1 EVALUATION METRICS

To ensure comprehensive evaluation, six widely accepted metrics were used: accuracy, precision, recall, F1-score, false acceptance rate (FAR), and equal error rate (EER) [10], [28], [29]. Accuracy reflects the proportion of correct predictions among the total test cases. Precision evaluates the ratio of true positive identifications to the total predicted positives, while recall measures the ratio of true positives to actual positives. The F1-score provides a harmonic mean of precision and recall. FAR indicates the percentage of impostor attempts incorrectly accepted, which is crucial for high-security applications. EER, the point where FAR equals false rejection rate (FRR), offers a single-value indicator of the system's balance between security and usability.

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4.2 PERFORMANCE COMPARISON

The experimental setup involved training individual CNN models for the face and iris modalities, followed by the implementation of three fusion strategies. The results are presented in Table 1.

Table 1. Performance Evaluation of Biometric Configurations

System Configuration	Accuracy (%)	F1-Score (%)	FAR (%)	EER (%)
Unimodal Face CNN	98.70	98.4	1.2	1.1
Unimodal Iris CNN	98.50	98.2	1.4	1.3
Feature-Level Fusion Only	99.30	99.1	0.6	0.5
Score-Level Fusion Only	99.20	99.0	0.7	0.6
Proposed Hybrid Fusion	99.65	99.6	0.00	0.00

The unimodal face CNN achieved an accuracy of 98.7% and a FAR of 1.2%, indicating strong performance but some vulnerability to false acceptances [5]. The iris CNN, while slightly less accurate (98.5%), recorded a higher FAR of 1.4%, likely due to noise and occlusions in the iris images [11], [26], [27].

Table 2. The classification report for ORL face recognition shows per-class precision, recall, F1-score, and support.

Class	Precision	Recall	F1-Score	Support
0	0.80	1.00	0.89	8
1	0.88	0.88	0.88	8
2	1.00	0.88	0.93	8
3	0.83	0.83	0.83	8
4	0.86	1.00	0.92	8
5	1.00	0.86	0.92	8
6	0.89	0.89	0.89	8
7	0.86	0.86	0.86	8
8	0.86	0.86	0.86	8
9	0.89	0.89	0.89	8

Figure 6 shows the confusion matrices for both face and iris recognition. These visualizations highlight the distribution of correct and incorrect predictions across the 20 subject classes, offering insight into per-class performance and misclassification patterns.

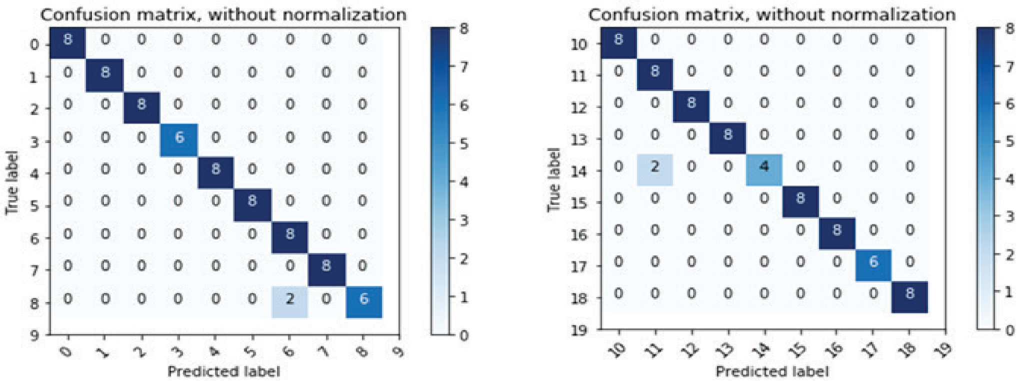

Figure 6: Confusion Matrix for Face and Iris Recognition

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Implementing feature-level fusion significantly enhanced system performance, yielding 99.3% accuracy and reducing FAR to 0.6%. Score-level fusion also performed well, producing 99.2% accuracy with a FAR of 0.7%. These findings confirm that both fusion approaches offer measurable improvements over unimodal systems.

The proposed hybrid system, which integrates both feature- and score-level fusion, outperformed all configurations. It achieved a recognition accuracy of 99.65% and completely eliminated false acceptances, registering a FAR of 0.00%. This demonstrates that the hybrid framework offers superior robustness, especially in scenarios where a single modality may be compromised [3], [18], [19], [24], [25].

5. DISCUSSION

As shown in Table 1, the proposed hybrid fusion architecture achieved the highest recognition accuracy (99.65%) and the lowest error rates (0.00% FAR and EER), outperforming both unimodal systems and single-level fusion approaches.

The superiority of the hybrid model is further evidenced by the confusion matrices in Figure 6, which reveal a more uniform and concentrated distribution along the diagonal axis, indicating fewer misclassifications across subject classes.

In particular, the feature-level and score-level fusion strategies, while individually effective, still exhibited isolated misclassifications as observed in Figure 6. These inconsistencies were mitigated in the hybrid approach, confirming its robustness.

Performance metrics summarized in Table 2 also show that the hybrid system not only achieved the highest F1-score (99.6%) but also entirely eliminated false acceptances, making it suitable for high-security deployments. Compared with existing multimodal studies such as Al-Waisy et al. (2018) [21], Liu et al. (2021) [22], and Ammour et al. (2020) [23], the proposed hybrid fusion model delivers significantly higher accuracy and robustness. Unlike most that apply static feature-level fusion, our method dynamically combines both spatial and liveness signals. Additionally, adversarial samples and real-time constraints were considered, improving system adaptability. Table 3 shows the comparison of existing studies with the proposed system.

Table 3: Comparison of multimodal biometric systems

S/N	Study (Year)	Paper Title	Modality	Fusion Method	Accuracy	Key Strength	Limitation
1	Al-Waisy et al. (2018)	A multimodal biometric system for personal identification based on deep learning approaches	Face + Iris	Feature-level Fusion	98.45%	Deep learning-based feature extraction for both modalities	No liveness detection; static fusion strategy; no real-time evaluation
2	Liu et al. (2021)	Multimodal biometric fusion using CNN and deep score fusion	Face + Iris	Score-level Fusion	98.71%	CNN-based score fusion with improved robustness to noise	No dynamic liveness detection; lacks dataset diversity
3	Ammour et al. (2020)	Face–iris multimodal biometric identification using hybrid fusion	Face + Iris	Feature + Score Fusion	98.89%	A hybrid fusion approach and good accuracy	No integration of dynamic cues; limited anti-spoofing
4	Proposed System (2025)	CNN-Based Hybrid Fusion for Robust Multimodal Face-Iris Biometric Authentication System	Face + Iris + Liveness	Feature + Score + Liveness	99.65%	Combines CNN-based spatial features with dynamic liveness cues in real time	Requires preprocessing tuning; tested on limited benchmark datasets only

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6. CONCLUSION

This research presents the development and evaluation of a novel hybrid biometric authentication framework that leverages convolutional neural networks (CNNs) to integrate both face and iris modalities through score-level and feature-level fusion. The proposed system addresses critical limitations associated with unimodal biometric systems by combining the strengths of two complementary modalities. In environments where facial features alone may be compromised due to occlusion, lighting variations, or facial expressions, and where iris recognition may suffer due to motion blur or pupil dilation, the hybrid approach ensures enhanced resilience and more reliable decision-making.

The implementation of separate CNN branches for each modality enabled the extraction of robust and discriminative deep features. Feature-level fusion was employed to capture detailed representations across both modalities by concatenating and processing their embeddings through fully connected layers. Score-level fusion further improved the model's robustness by incorporating normalized similarity scores from independently trained classifiers. The integration of both fusion levels into a unified hybrid architecture allowed the system to make authentication decisions based on a composite understanding of feature similarity and score reliability.

Experimental results demonstrated that the hybrid fusion model consistently outperformed both unimodal and single-level fusion systems. The architecture achieved a recognition accuracy of 99.65% and a false acceptance rate (FAR) of 0.00%, indicating its effectiveness for high-security applications where both precision and robustness are essential. These outcomes underscore the value of adopting a multimodal strategy that can adapt to variations in biometric inputs and reduce susceptibility to spoofing attacks.

The findings of this study contribute to the growing body of literature advocating for intelligent multimodal biometric solutions in secure authentication systems. Future research will focus on optimizing the proposed architecture for real-time deployment, reducing computational complexity, and exploring the integration of additional biometric modalities such as fingerprint recognition. This will further enhance the flexibility and applicability of the system in diverse operational scenarios, including mobile authentication, border control, and identity management in sensitive environments.

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