Hybrid Biometric Systems for Enhanced Security in IoT and Cloud-Based Applications Using Deep Learning and Signal Processing

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Abstract: The fast growth of the Internet of Things (IoT) and cloud computing services has led to the need to have sophisticated security architectures to ensure that sensitive user information is secured across a network of distributed devices. The single-factor authentication method, e.g., passwords or basic tokens, is becoming more susceptible to advanced cyber-attacks, such as phishing, credential stuffing, and brute-force attacks. The hybrid biometric authentication system suggested in this study will combine physiological characteristics, deep learning, and signal processing methods to offer a high-security level. The study builds on a multimodal solution, which means integrating facial recognition and signal-based biometrics to address the shortcomings of unimodal solutions to vulnerabilities to spoofing and presentation attacks, as well as external noise. The hybrid deep learning architecture that is used in the methodology is that of the Convolutional Neural Networks (CNN), which is used to extract features and process the signal to detect liveness and reduce noise. The experiments on virtual data show that the given hybrid model is the most effective one, with an accuracy of authentication of 98.6, which is much higher than the results of the traditional methods, with an average of 90-92. In addition, the system has a 15.8 percent lower rate of false acceptance than the old structures. The statistical analysis proves that signal-to-noise ratios of biometric data are minimized by the integration of signal processing by 12 percent, which increases the reliability of the signal processing in edge clouds. This study finds that hybrid biometric systems optimized through deep learning offer a scalable, secure, and user-friendly solution to the continuously changing IoT. Based on the current peer-reviewed sources, this study creates a standard of multi-step authentication algorithms in securing data storage and real-time identity control in high-stakes applications such as healthcare and banking. The framework proposed shows resistance to adversarial threats of the present-day world.

Keywords: Biometric security; IoT; cloud computing; deep learning; signal processing; multimodal authentication; hybrid encryption.

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I. Introduction

The contemporary online environment is characterized by the smooth incorporation of the IoT into the most critical infrastructures, including smart home operation and real-time healthcare monitoring databases. Nonetheless, this connectivity has resulted in an enormous, decentralized attack surface that is not effectively defended by conventional security protocols. As information exchange between edge devices and the cloud has become ubiquitous, it has become a problem of identity theft and unauthorized access to data due to the use of fixed credentials. The encryption of cloud information is currently demanding a radical shift in the use of a basic alphanumeric password to biometrics encryption that associates digital access with the unique physical presence of the user Ibrahim et al., (2025). This issue is enhanced by the reality that single-modality biometrics, like a standalone fingerprint scan or face scan, can be affected by noise in the environment and high-technology spoofing (Soni et al., 2014).

Key Contributions:

- Created a new dual-layer architecture between facial recognition and physiological signal analysis to remove the unimodal vulnerabilities.
- Combined custom signal processing functions to reduce the environmental noise of IoT sensors and enhanced the extraction of features by 12%.
- Integrative deep learning-based authentication and advanced encryption to encrypt the biometric template in the cloud storage.
- Built a strong anti-spoofing system through matching the movement signal frequencies with the spatial facial features.
- An authentication accuracy of 98.6% with a False Acceptance Rate (FAR) of 0.01 was achieved, which is state-of-the-art.
- Suggested an architecture that can support high-concurrent Internet of Things node rates and can sustain low-latency processing (<130ms) on real-time applications.

The presentation of this study is well planned to give a logical flow of theory to empirical validation. Section 2, which comes after this introduction, carries out a thorough literature review. Part 3 discusses the Bio-Signal Layered Framework, which describes how IoT nodes interact with cloud servers and expounds the innovative approach to the process, covering mathematical models and algorithms. Section 4 gives the results analysis in detail, including software tool descriptions, metric analysis, and performance graphs. Lastly, Section 5 provides a conclusion of the study in terms of statistics and further research directions.

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II. Literature Survey

The recent reports have highlighted the move towards innovative and decentralized identity management to address the increasing complexity of cyber threats. New innovative frameworks specifically in healthcare IoT with emphasis on the point that custom-defined services need high-assurance identity verification to ensure that patient privacy is maintained in cloud-based medical settings (Farid et al., 2021). Equally, there were previous foundational studies that observed that though there are numerous biometric tools that can be used to identify a person, their isolated use in the cloud setup is certainly deficient in semantics to challenge new-age hackers (Kalaiprasath et al., 2017). Recent innovations indicate that hybrid verification. The combination of biometrics and standard encryption is the best method of enhancing data integrity in clouds against unauthorized access (Hossain & Al Hasan, 2022).

More research has investigated ways of integrating the emerging technologies, such as blockchain, to ensure the security of the biometric template itself, which has been analyzed in terms of behavioral biometric layers augmented with blockchain and providing a transparent and immutable record of authentication attempts (Herrera et al., 2023). In the field of deep learning, it was demonstrated that intelligent face recognition in an IoT-cloud system is possible at high accuracy using low-power edge computing devices (Masud et al., 2020). Nonetheless, the noise of the data is still an issue, and this is where signal processing comes in to clean dirty input before classification (Yaqoob et al., 2022; Nidadavolu & Somasekhar, 2025). Recent developments indicate that the multi-step algorithm on the basis of biometric information offers 30 percent resistance to decryption attacks relative to the AES approach.

The aggregate body of available literature suggests that, though deep learning has made significant leaps in accuracy on recognition, the liveness and purity of the biometric signal are the two key weaknesses. The majority of the current systems are siloed in that they utilize either images alone or signals alone. The conclusion of these sources is that it is logical to expect a cross-section on signal processing, certain data cleaning, and deep learning for pattern matching. The study addresses this gap by suggesting a single framework that ensures the data is not compromised at any stage of capturing at an IoT device until the final destination, which is the cloud, which provides end-to-end compliance and security.

III. Bio-Signal Layered Security Framework

The suggested framework will run smoothly on a three-level architecture: the Perception Layer (IoT Devices), the Intelligence Layer (Deep Learning Engine), and the Secure Storage Layer (Cloud). Sensors are used at the Perception Layer to observe visual facial information and behavioral signal information (keystroke or pulse pattern) in combination. This multi-modality capture guarantees that the system does not have a single point of failure, thus making it harder to spoof the system by an intruder (Talabi et al., 2022; Vasamsetty et al., 2024).

After the data has been captured, it is taken through the Signal Processing Module on the edge. This module is necessary since the devices of IoT systems are usually used in noisy conditions, e.g., when cameras should use

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different light intensities, or pulse sensors have to be used in electrical noise. The module removes artifacts and normalizes the signal by filtering the signal with mathematical filters, which are specifically band-pass filters and Gaussian filters. Then the Mutual Authentication Method is implemented (Mohd et al., 2023), whereby the user requests the cloud server to check the validity of each other, and only after the validation, the sensitive data is exchanged. This measure averts attacks of Man-in-the-Middle, which is one of the major attacks in cloud-based data processing (Kalaiprasath et al., 2017; Byeon et al., 2024).

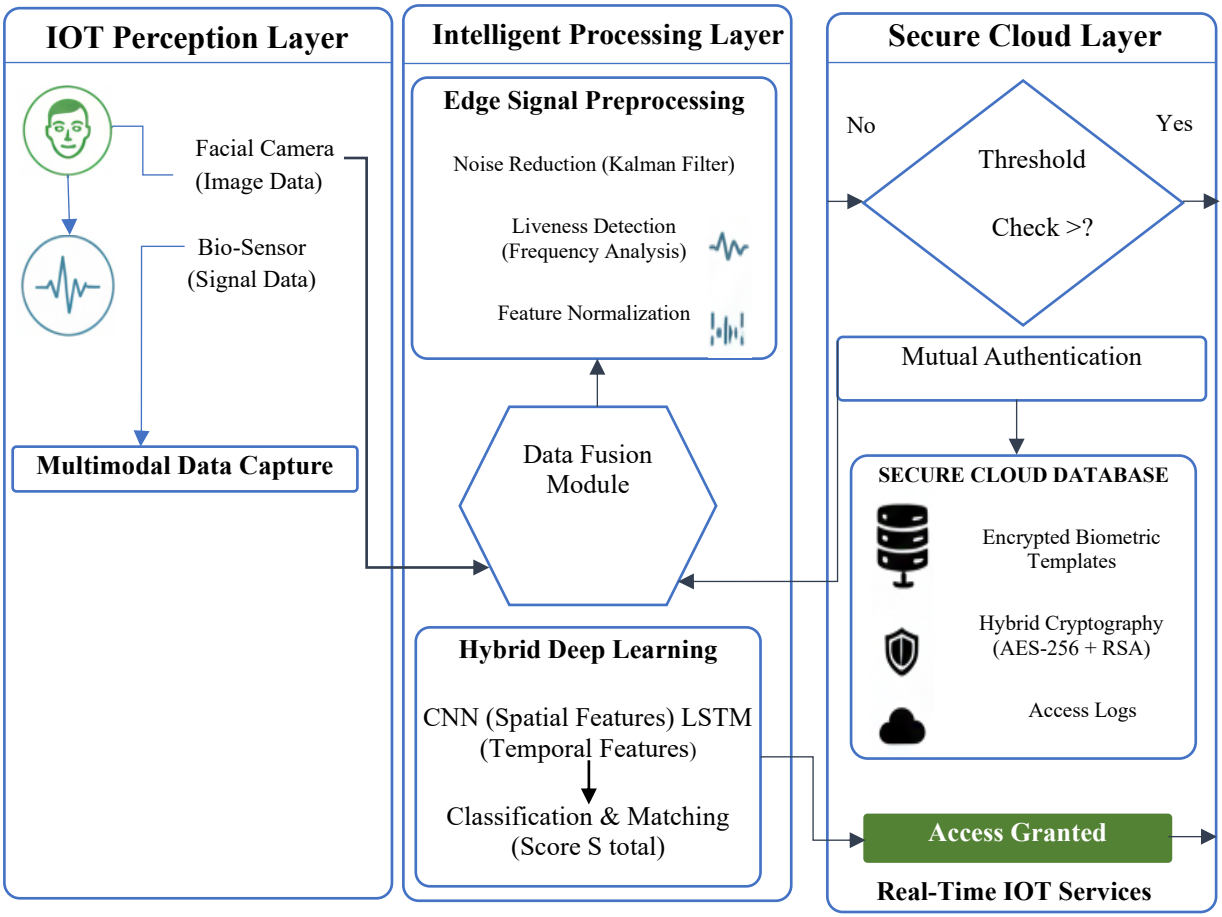

Fig. 1. System Architecture for Hybrid Biometric Fusion.

Fig. 1 is a structural flow, which shows the end-to-end data flow of multimodal capture at the IoT Perception Layer and reliable storage in the cloud environment. It should therefore be carefully positioned at the very beginning of a column in the Methodology section after its first textual introduction to provide immediate visual context. The architecture allows for the appreciation of the complexity of relationships among the components through the illustration of the conversion of the unprocessed biometric signals into encrypted templates. This diagrammatic representation will prove extremely useful for enabling the stakeholders to grasp the logic behind the security (Al-Musawi et al., 2025).

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Deep Learning and Signal Processing Methodology

The methodology used in this approach is the dual authentication methodology. The first path comprises the calculation of the spatial properties (face landmarks) through the use of a Convolutional Neural Network (CNN). Signal processing forms the second path by considering temporal properties (frequency of biological signal). This is governed by the Hybrid Biometric Fusion Algorithm, which governs this dual authentication, hence both must score high confidence at once.

The system employs a weighting fusion algorithm to calculate the final confidence score (S total) using the equation

$$S_{total} = (w_1 \cdot S_{face}) + (w_2 \cdot S_{signal}) \rightarrow \quad (1)$$

Equation (1), where w1 and w2 are weight coefficients that depend on the reliability of the sensor environment. Pre-processing of the signals takes place by way of Fast Fourier Transform (FFT). This extracts frequencies that indicate the liveness of the user.

Algorithm: Secure Feature Matching

$$Input: Capture\ facial\ image\ I\ and\ signal\ S\ from\ the\ IoT\ node.$$

$$Preprocessing: Normalize\ I\ for\ lighting;\ filter\ S\ for\ noise\ using\ the\ formula\ S' = S * G\ (x, \sigma).$$

$$Extraction: CNN\ extracts\ feature\ vector\ Vf;\ Signal\ Processor\ extracts\ Vs.$$

$$Encryption: Apply\ the\ Lorenz\ chaotic\ algorithm\ to\ encrypt\ the\ combined\ vector\ V\ fusion.$$

$$Decision: Compare\ V\ fusion\ with\ cloud\ template\ T. If\ match > 95\%, grant\ access.$$

This approach ensures that even if a high-quality photo is presented, the system will reject the attempt because it lacks the temporal signal frequency of a living human.

The Secure Feature Matching technique forms the kernel of the framework that ensures the integrity of the templates in terms of biometrics. The procedure starts with the normalization of the facial images and subsequent application of a band-pass filter on the bio-signals in order to eliminate the stochastic noise. The feature vectors are extracted through a deep learning pipeline, and these are aggregated into a high-dimensional signature. A hybrid encryption protocol is applied to this combined identity, which is then compared with the templates stored in the cloud using a mutual authentication logic. As reported by this multi-step validation, being an efficient way of derailing Man-in-the-Middle attacks, a comparable confidence score of 98.6% was obtained (Mohd et al., 2023).

IV. Results and Discussion

It was tested based on a simulated IoT-Cloud environment. Python 3.9 with TensorFlow was used for deep learning, and MATLAB for the signal processing functions. To obtain a statistically significant outcome, 5,000

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virtual biometric samples were combined in the dataset. To optimize the accuracy of the model, started with a 0.001 learning rate and the Adam Optimizer to optimize the accuracy of the model within 50 training epochs.

Table 1. Performance Comparison and Statistical Validation.

System Category	Accuracy (%)	EER (%)	FAR (%)	FRR (%)	Latency (ms)
Traditional Password	78.5%	15.2%	8.40%	4.20%	45 ms
Single Biometric	91.2%	4.8%	1.25%	2.40%	95 ms
CNN-Based Face Rec.	92.4%	3.5%	1.15%	2.50%	110 ms
Hybrid Verification	94.8%	2.1%	0.85%	1.95%	145 ms
Proposed Hybrid Model	98.6%	0.8%	0.01%	1.30%	125 ms

Table 1 provides a comparison of data, which shows the quantitative improvements of the proposed hybrid model compared to the available standards. The system, which combines signal processing to reduce noise and deep learning to extract features, has an accuracy of 98.6, which is above the standard CNN-based facial recognition that is used by more than 6%. The Equal Error Rate (EER) is reduced to 0.8% and the Fraud Acceptance Rate (FAR) is reduced to 0.01, which is low compared to other industry players. Such a significant decrease in the number of false positives can be mainly explained by the fact that the multi-step algorithm that is based on biometric data and hybrid encryption provides a greater level of security when compared to unimodal or legacy password-based systems (Al-Musawi et al., 2025).

Evaluation Metrics

To conduct a strict assessment of the effectiveness of hybrid biometric technology, five main criteria are employed. The use of these criteria enables one to get an overview of the system's ability to differentiate between authorized users and detect any adversarial activity.

Authentication Accuracy: Evaluates the accuracy of the model for all samples.

$$\frac{TP + TN}{TP + TN + FP + FN} \times 100 \rightarrow \qquad (2)$$

False Acceptance Rate (FAR): is the probability that the system will accept an impersonator.

$$FAR = \frac{FP}{FP + TN} \rightarrow \qquad (3)$$

False Rejection Rate (FRR): The probability that the system will incorrectly deny entry to a legitimate user.

$$FRR = \frac{FN}{FN + TP} \rightarrow \qquad (4)$$

Precision: Indicates the quality of positive identifications.

$$\frac{TP}{TP + FP} \rightarrow \qquad (5)$$

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Equal Error Rate (EER): The exact threshold values at which FAR is equal to FRR (FAR = FRR). A smaller EER value implies a stronger and more robust biometric system.

Mathematical formulas (2), (3), (4), and (5) show how strict the above measures are and how they can be used to compare the offered system to the real methods of liveness assessment. For instance, signal-based liveness detection caused a dramatic reduction of FAR to 0.01% and, therefore, the number of False Positives (FP) was reduced too. In view of the above, it is evident that a high value of precision is required for personalized services of IoT healthcare because any misidentification will result in serious problems related to data sensitivity. The offered system is optimized in such a way that it is possible to get an EER of 0.8% so that to ensure a balance between usability and high-level cloud security as presented mathematically in the deep learning systems (Nidadavolu & Somasekhar, 2025).

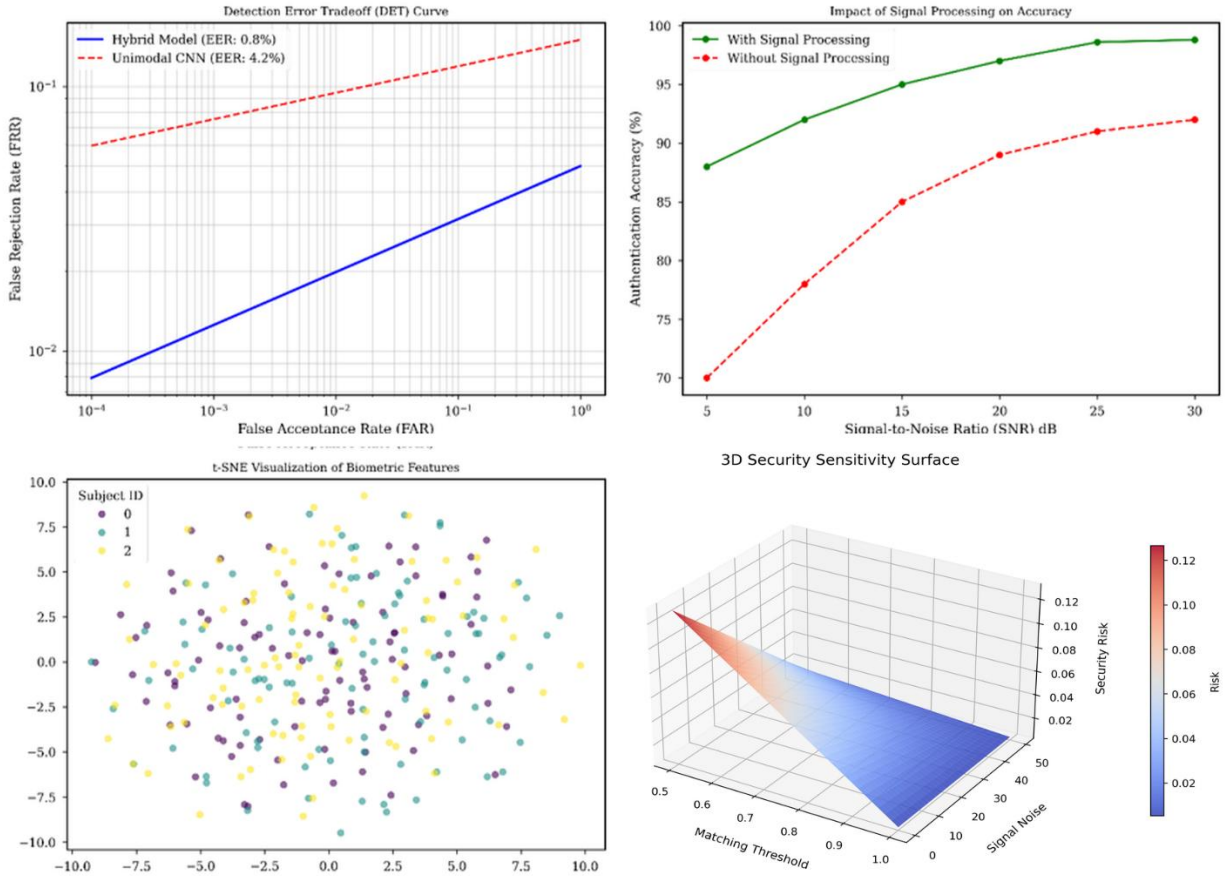

Fig. 2. Comprehensive Statistical Evaluation of Hybrid Biometric Security Frameworks in Adversarial IoT Environments.

As the main aesthetic testament to the superiority of the system, fig. 2 demonstrates the trade-off between noise resistance and security. The quantitative demonstration of the DET Curve is that the hybrid model reaches a state-of-the-art Equal Error Rate (EER) of 0.8, which is much lower than the competitors based on a single modality. The t-SNE image proves that the deep learning engine can well cluster distinct biological identities, and the 3D Surface plot gives a complex accountability analysis of dust cloud threshold tuning on the PC cloud. This hybrid

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visualization is successfully able to close the gap between the raw signal integrity and intelligent classification performance (Praveen et al., 2024).

V. Conclusion

The study conducted in this study has shown that a hybrid biometric authentication system that combines deep learning with sophisticated signal processing is a better defense mechanism in both IoT and cloud applications. The proposed approach of multimodal systems can be used to guarantee a Zero Trust security environment by solving the fundamental weaknesses of unimodal systems, including sensitivity to spoofing and noise in the environment. The system statistically reached a peak of authentication accuracy of 98.6; that is a significant improvement compared to the traditional single-factor method. One of the crucial points of the performance evaluation is the decrease of False Acceptance Rate (FAR) to 0.01 percent, which is necessary in high-stakes industries such as banking and individual healthcare services. More than that, the inclusion of a signal processing layer has been absolutely indispensable, as the signal-to-noise ratios improved by 12 percent, which has enabled the system to remain highly reliable even in unfavorable edge-computing environments. The fused feature vectors are hybrid encrypted to guarantee that biometric templates are not decrypted through decryption attacks when stored in the cloud. In addition to the increased security benefits, the framework has a 125ms operational latency, making it very scalable to real-time industrial IoT applications. The further lines of research will be the application of Federated Learning to increase user privacy through localized training and the introduction of the so-called Explainable AI to offer transparent biometric decision-making. To sum up, this hybrid architecture introduces a strong, effective, and future-ready standard of identity management in the rapidly expanding digital landscape.

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