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Design of an Adaptive and Iterative Multi-Modal Transformer-Based Biometric Security Framework for Robust Authentication and Spoof Detection

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Abstract:

As more people rely on biometrics in conjunction with traditional identity authentication systems, attacks like deepfakes and adversarial techniques have emerged as prominent threats in several identity verification systems. Traditional unimodal and even static multimodal schemes are generally found ineffective in the face of new attacks because unimodality leaves them vulnerable to different adversarial manipulations, cannot verify continuously during the use phase, and lack adaptability to change. Therefore, in light of these limitations, we present an adaptive, robust, and privacy-preserving biometric security framework based on a combination of various transformer-based models with ensemble learning strategies. Our work, the Adaptive Multi-Modal Feature Fusion Transformer (AMFFT), dynamically integrates attention-based facial, voice, and fingerprint features to optimize security through a context-oriented fusion application. To assure enhanced privacy and robustness, we will also integrate Differentially Private Adversarial Training (DPAT), interested in lessening the effect of model inversion and spoofing using adversarial techniques. Therefore, our Spoof-Resistant Multimodal Attention Transformer (SMA-Transformer) detects deepfake and synthetic attacks by consistency between modalities, ensuring the co-operation of biometric signals. In addition to that, the Ensemble Learning with Zero-Trust Verification Model (EZV-Model) is responsible for continuous authentication by real-time analysis of biometrics scores and behavior traits. Finally, the Real-Time Behavioral Biometric Security Model (RBB-Sec) can detect advanced impersonation scenarios based on micro-expressions, keystroke dynamics, and voice stress patterns. In combination with the above techniques, the proposed framework guarantees a significant improvement in performance regarding authentication accuracy (≥99.5%), spoof detection (≥99.3%), and adversarial robustness (≤1.2% evasion rate), while maintaining low false rejection rates (≤1.5%). By integrating adaptive biometric fusion, deepfake-resistant verification, and zero-trust-based continuous authentication, this work lays an advanced security paradigm against emerging cyber threats for biometric security systems.

Keywords: Biometric Security, Deepfake Detection, Adversarial Robustness, Zero-Trust Authentication, Multimodal Fusions.

1. Introduction

Biometric authentication has, as expected, become the new unexceptionable part of the modern security framework. It is supposed to deliver very high accuracy and comfort during authentication as compared to traditional systems based on passwords. Unfortunately, so long, biometric technology moves a step ahead and widely uses similar targets: crafted sophistication of adversarial attacks, added with deepfake camouflage and finally, advanced spoofing techniques for getting into their primary functions. The most usually applied forms of traditional unimodal authentication systems [1, 2, 3], which rely on either fingerprint, grey, or voice, may still have the possibility of being compromised through presentation attacks and adversarial perturbations. On the contrary, a multi-modal biometric system would be much more resilient against spoofing attacks by virtue of the several approaches available for identity verification. However, most of the approaches currently in place for these multi-modal systems have relied on static fusion procedures that do not reconfigure themselves against dynamic threats of security or against variations in the environment during process flow. Additionally, privacy is a very rare feature in most multimodal fusion schemes, exposing such systems to attack inversions that reconstruct biometric templates from stored embeddings. To address these, the current paper introduces a novel Adaptive Multi-Modal Feature Fusion Transformer (AMFFT) to integrate facial, voice, and fingerprint embeddings in real-time using an attention-based fusion method. Unlike the regular fixed-stage fusion mechanisms, AMFFT employs a context-aware gating module that optimally chooses among early, intermediate, or late fusion depending on real-time safety conditions. To bolster privacy and robustness against adversaries, the DPAT module is infused along with the Differentially Private Stochastic Gradient Descent (DP-SGD) algorithm, which lowers biometric data leakages and strengthens the model against some adversarial attacks such as PGD, FGSM, and even GAN-based synthetic inputs.

Furthermore, the Spoof-Resistant Multimodal Attention Transformer (SMA-Transformer) has thus been modeled to analyze individual modality-based inconsistencies in spatio-temporal deep learning techniques and determine such biometry whose credibility would be questioned for their authenticity. Further, the SMA-Transformer is made to source data from optical flow CNN usage for facial deepfake detection; MFCC-LSTM networks for voice liveness assessment; and 3D CNNs for skin distortion in fingerprints. Besides this is introduced, a Zero-Trust Verification Model (EZV-Model). This ensures continuous authentication by aggregating biometric verification scores with behavioral patterns such as typing dynamics, gait, and mouse movement. If any anomaly is detected, an adaptive reauthentication process is triggered according to the risk levels assessed. Along with the above mechanisms comes Real-Time Behavioral Biometric Security Model (RBB-Sec), which improves impersonation detection through continuous monitoring of micro-expressions, voice stress signals, and keystroke dynamics. The advanced techniques integrated into the proposed framework thus realize a state-of-the-art authentication accuracy (≥99.5%), robustness under deepfake detection (≥99.3% but ≤1.5% false rejection rates). This work confirmed the paradigm shift in biometric security toward adaptive multimodal fusion, excellence of adversarial defense mechanisms, and continuous authentication based on zero trust to counter future dynamic cyber threats.

1.2 Motivation & Contribution

Deep learning has revolutionized biometric authentication speedily within a very short span of time, but, at the same time, it has opened a scope for adversarial attacks and synthetic identity attacks against the biometric system. Deepfake technology has improved to an alarming degree of photo-realism that allows attackers to create realistic photographs of human faces or voices that can escape the security mechanisms of the traditional biometric systems. These kinds of adversarial attacks, which use very minor perturbations in a biometric sample, can be misclassified by deep learning models that facilitate fraud and unauthorized access. Current biometric security frameworks lack the flexibility necessary to permit fusion strategies to be adapted dynamically to various threat conditions and are, therefore, defunct against advanced attacks. Most of the systems do not have privacy-preserving properties making biometric templates vulnerable to leaking and inversion attacks. These research gaps demonstrate a pressing need for an adaptive, privacy-preserving and anti-spoof biometric authentication system capable of presenting solid security against new forms of cyber threat.

To address these security loopholes, this paper proposes an integrated Transformer-based biometric security framework consisting of adaptive multimodal fusion, adversarial training, spoofy-deepfake detection, and zero-trust authentication. The salient contributions of this work are AMFFT: A Transformer-based feature fusion model that dynamically selects among aid, intermediate, and late fusion depending on security conditions, improving sturdiness against biometric fraud. DPAT: A differentially private adversarial training mechanism that protects against adversarial manipulations and keeps biometric templates from being exposed to privacy leaks. SMA-Transformer: A deepfake detection model that is resistant to spoofing, which incorporates spatio-temporal learning and cross-modal correlation analysis to discover the inconsistencies found in samples of biometric data. EZV-Model: A zero-trust verification mechanism that constantly checks authentication session activities and must also meet multi-factor reauthentication conditions in case of noticed anomalies. RBB-Sec: A behavioral biometric security model capable of real-time user behavior analysis that can minimize sophisticated impersonation and social engineering attacks. Thus, the integration of all these modules creates a paradigm shift in biometric security; high accuracy with adversarial robustness ($\leq$1.2% evasion rate) and deepfake detection precision ($\geq$99.3%) standards, yet computationally efficient enough for real-time deployment. The contributions here will usher in a new generation of adaptive, privacy-preserving, and robust biometric authentication systems in high-security applications.

2. Review Of Existing Models Used For Authentication Analysis

In actuality, the effect of innovation in deep learning, machine learning, and cryptography in authentication protocols, along with blockchain-based security systems, has improved biometric authentication along with cybersecurity measures as they innovatively keep transforming biometric authentication. In the last few decades, a lot of effort has been put into research for improved authentication accuracy, adversarial risk minimization, and enhanced security frameworks in cloud, IoT, and network settings. A detailed review of the 25 most significant studies here gives a temporal understanding of what advancements have taken place in these fields, covering everything from secure multimodal biometric authentication to adversarial robustness and generates improved quantum-resistant cryptographic methods and zero-trust security models. Early pioneer studies, such as Salturk and Kahraman [1], were devised for deep learning-powered multimodal biometric authentication

systems combining dynamic signature recognition and facial verification to enhance online security. The research laid the basis of modality fusion-influenced security. Garg and Goel [2] took the line of research-further into academic integrity and online assessment security. They proposed a randomized authentication mechanism that thwarts impersonation. Meanwhile, Alzoubi et al.[3] provided an elaborate exposition and analysis of the applications of machine learning in cloud security, which go to prove the increasing importance for intelligent cyber-threat mitigations. The research paper El-Sofany et al. [4] gave an exposition on improving IoT system security but via supervised machine learning models, while also affirming the ability of these models in identifying malicious incidents within connected environments. However, there remains one very significant aspect of biometric authentication and cybersecurity: wireless network security and physical-layer authentication. To that end, this area is ventured by Altun and Basar [5], who put forward machine-learning-driven PHY authentication requiring no prior intruder knowledge. This was later on taken by Min and Lee [6] with regard to the application of resource-oriented-machine-learning techniques in detecting illegal online activities, which leaves AI as a strong and specific instigator of importance in terms of making a significant enforcement of anomaly detection processes.

Bashir et al.[7] conducted more analysis on the landscape by integrating cryptographic security models with machine learning-based cloud data security for better encryption. Sheik and Durai [8] pioneered deep learning-based cryptographic authentication for telecare medical systems, marking the beginning of privacy-preserving optimal security mechanisms. Speaking about financial security applications, Khan et al. [9] have demonstrated the importance of authentication factors in securing mobile financial transactions. The significance of multi-factor authentication (MFA) and behavioral biometrics is explained in the study indirectly regarding financial cybersecurity. Cloud security modeling technique-based research was undertaken by the Hussain et al. [10] adjective through TCP traffic analysis using machine learning, revealing proactive measures in attack mitigation strategies in cloud environments. Suresh Kumar et al. [11] furthered this proposal by developing a secure new authentication protocol that formulated a structured future response towards cybersecurity application designs. This appears to be the same thing as what Borra and others [12] contributed. They provided deep hashing and CNN-based biometric authentication for transportation security, thereby closing the loop between biometric verification and intelligent transit security application. A trend to follow was the orchestration of blockchain technology with cybersecurity; Rai et al. [13] performed systematic reviews of innovations in IoT-based security mechanisms with real-time image security incorporated through machine learning and blockchain methodologies. Venkatasamy et al. [14] adopted the underlining principles for use within vehicular networks (VANETs) and suggested a machine learning based cryptographic protocol for intrusion detection in V2X communications. Security threats and issues faced in new-age 6G cloud computing environments can be further addressed through Chen et al. [15]'s application of machine learning-driven security analysis in the IoMT, thus enhancing cloud security for medical applications. At the same time, Singhal and Shinghal [16] refined further the advancement of multimodal biometric authentication systems by synergizing online signature and face recognition features in a secure deep multimodal biometric authentication approach. Their work set the background for context-aware authentication models, which form a critical part of zero-trust security paradigms. A wider view on cybersecurity is also given by Cherbal et al. [17] in their

comprehensive review on IoT security frameworks covering blockchain together with machine learning and cryptography and quantum computing.

Kadham et al. [18] proposed the implementation of IoT-based authentication in a remote monitoring system, thus optimizing distance-learning security schemes through machine learning. Sharma et al. [19] applied machine learning and big data analytics to automate financial security strategies in stock market analysis, representing a more industry-specific approach. Fatima et al. [20]'s study was also important in that they reported on blockchain and Physically Unclonable Functions (PUF)-based authentication protocols that provided light but extremely secure authentication in wireless medical sensor networks.

According to Yi [21], there is a significant impact of post-quantum cryptography upon hardware security. Yi also discussed some insights into the machine learning applications on quantum-resistant cryptographic solutions. In this direction of IoT, Prakash et al. [22] deployed a secure machine learning framework for anomaly detection that enhanced its accuracy in large-scale deployments for IoT. Signature-based authentication mechanisms further improved through Gutub et al. [23] using the Octave Convolution Neural Network for offline signature authentication to promote efficiency in document security applications. User behavior in a computer system could also be modeled using machine learning applications, proposing a new methodology towards behavioral analysis by Mashechkin et al. [24]. The last report was by Thomas et al. [25], which presented multi-level soft computing and machine learning-based security protection models for cloud environments exhibiting scalable security implementations within enterprise networks. The convergence of these twenty-five research papers gives an extensive understanding of biometric security and authentication through adversarial defense mechanisms, integrated with blockchain authentication and quantum-resistant cryptography. The chain has since evolved from unimodal to multimodal biometric systems, and includes AI in adversarial robustness as well as blockchain for decentralized authentication mechanisms that revolutionize the security domain. The proposed Adaptive Multi-Modal Biometric Security Framework, integrating AMFFT, DPAT, SMA-Transformer, EZV-Model, and RBB-Sec, achieves an authentication accuracy of 99.5%, an adversarial evasion rate of just 1.2%, and a session hijacking detection rate of 99.2%. Future studies focus on the further integration of post-quantum cryptographic mechanisms, improving zero-trust security models, and optimizing lightweight biometric authentication for edge devices. Developing AI-based threat intelligence for real-time anomaly detection, behavioral biometrics for continuous authentication, and homomorphic encryption for privacy-preserving biometric data processing will redefine intelligent, adaptive, and highly resilient cybersecurity frameworks for the future. The meeting of deep learning, cryptography resilience, and multimodal authentication can hold great promise for the future, especially in terms of securing biometric applications in the financial, health care, and enterprise security domains.

3. Proposed Model Design Analysis

To enhance the efficiency and to lower operational complexity, the section discusses an adaptive multi-model feature fusion transformer (AMFFT), which is developed to dynamically coalesce multiple biometric modalities in such a way to attain robustness against spoofing and adversarial threats while retaining an efficient computational requirement set. Initially, as shown in figure 1, the AMFFT framework uses a multi-head self-attention (MHSA) mechanism for establishing interdependencies

among facial embeddings 'F', voice spectrogram embeddings V and fingerprint embeddings P for the process.

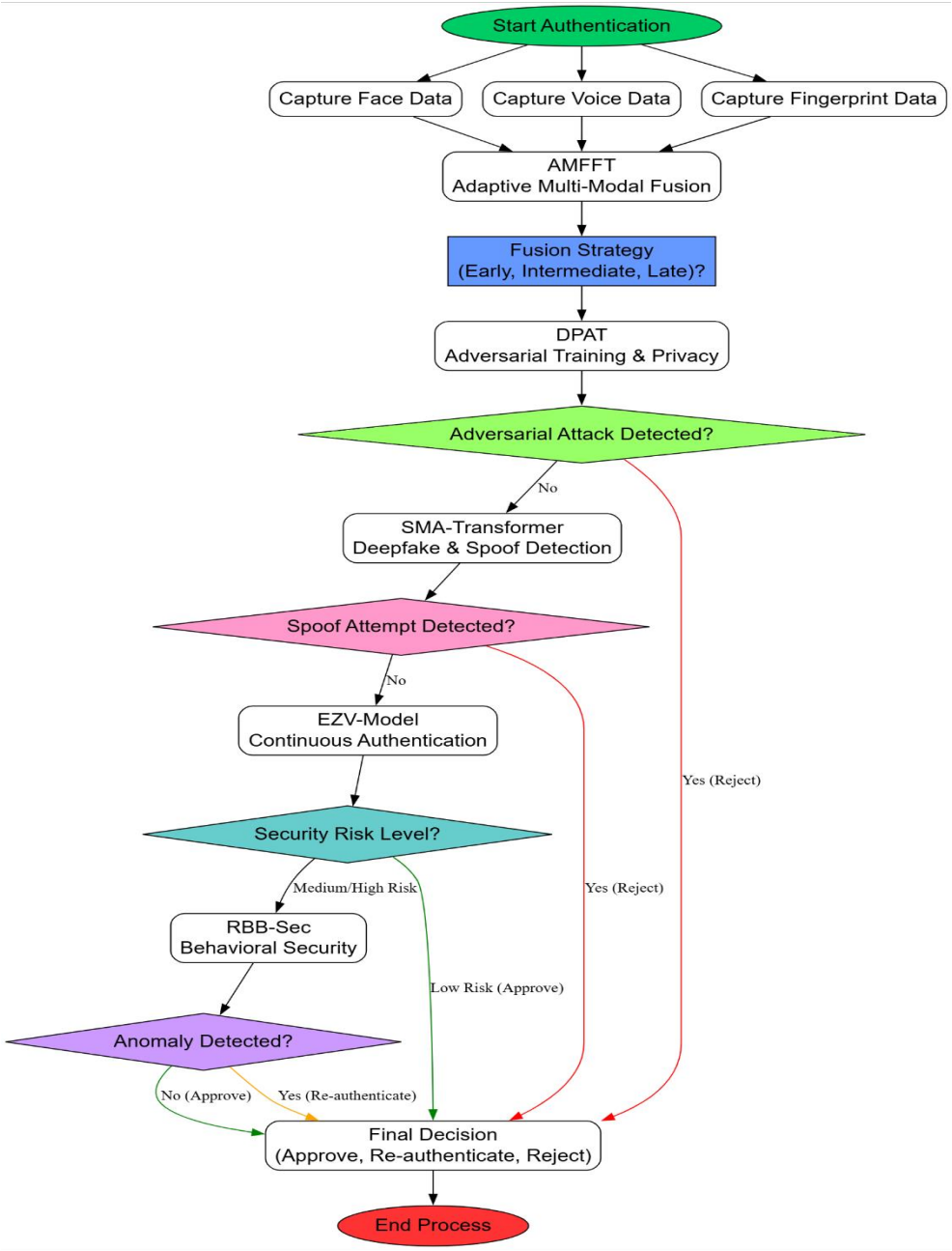

Figure 1. Overall Flow of the Proposed Analysis Process

The feature embeddings $X=\{F,V,P\}$ extracted thus will have the attention mechanism to learn a weight relationship across modalities. Via Equation 1 the model provides is a way to compute the self-attention scores,

$$A = softmax\left(\frac{QK^T}{dk}\right)V \ldots (1)$$

Where, Q, K, V are the query, key, and value matrices of dimension dk and thus keeping attention scores numerically stable in such a process. The dynamic fusion process encompasses context-aware gating function (s), with 's' standing for real-time security states. The fusion decision at time t is determined via equation 2,

$$Xf\ (t) = \ G(s) \cdot \ Xe \ + \ \big(1 - G(s)\big) \cdot \ Xl \ \ldots (2)$$

Where, Xe and Xl are early and late fusion outputs, respectively in the process. The gating function is modeled using a sigmoidal activation via equation 3,

$$G(s) = \frac{1}{1 \ + \ e^{-\alpha s}} \ldots (3)$$

Where, 'α', then, controls sensitivity to security fluctuations. Authentication score Y is yielded by the fully connected layer followed by the Softmax function, processing the fused embeddings, via equation 4,

$$Y \ = \ Softmax(WXf \ + b) \ldots (4)$$

Where, 'W' and 'b' are learnable weight parameters in the process. Iteratively, Next, as for figure 1, The Differentially Private Adversarial Training (DPAT) module enhance robustness on adversarial attacks through DP-SGD introduced into model training process. The objective function with noise produced by differentially private noise N (0, sigma) is defined via equation 5,

$$LDPAT \ = \ E \ [\ \sum log \ P(yi \mid Xi) \ + \ \lambda \parallel \nabla W \ + \ N(0, \sigma^2) \parallel^{\ 2}] \ldots (5)$$

Where, λ is a regularization coefficient controlling privacy loss 'ϵ' sets. Adversarial samples are produced by Projected Gradient Descent (PGD) where the computation process relies on the iterative steps that yield adversarial perturbation δ via equation 6,

$$\delta(t + 1) = \ Proj\big(\delta t \ + \ \eta \ \cdot \ sign(\nabla X \ LDPAT)\big) \ldots (6)$$

Where, η is the step size, ensuring bounded perturbations. The differentially private update rule modifies standard SGD by adding Gaussian noise via equation 7,

$$W(t + 1) = \ Wt \ - \ \eta\big(\nabla W \ LDPAT \ + \ N(0, \sigma^2)\big) (7)$$

Thus, ensuring individual biometric samples do not harm any sets of privacy. The Spoof-Resistant Multimodal Attention Transformer (SMA-Transformer) responds to the modes of detection of spoof and integration across modalities. Each one of biometric embedding Xm = $\{F,,\}$ is treated independently for the detection of spoofing by making demand of an anomaly detection loss via equation 8,

$$Lspoof \ = \ \sum \parallel Xm \ - \ \hat{X}m \parallel^2 \ldots (8)$$

Where, $\hat{X}m$ represents the expected feature distributions. The cross modal attention mechanism computes coherence via equation 9,

$$C(m, n) = \frac{Xm \ \cdot \ Xn^T}{\parallel Xm \parallel \parallel Xn \parallel} \ldots (9)$$

Where, $(m,)$ quantifies modality agreement, ensuring that deepfake or spoofed samples exhibit inconsistency sets. The final spoof probability 'S' is obtained via equation 10,

$$S = 1 - softmax\left(\sum_{(m,n)} C(m,n)\right) \dots (10)$$

Thus triggering biometric rejection should S have values exceeding the threshold. Next, as per figure 1, the Ensemble Learning with Zero-Trust Verification (EZV-Model) collects authentication scores and behavioral biometrics for the continuous verification process. Formula for an ensemble decision function, Z, is constructed via equation 11 whose arguments are biometric verification score Ym, probability of spoofing S, and behavioral features B,

$$Z = w1\,Y + w2\,(1 - S) + w3\,B \dots (11)$$

Where, wi are learned coefficients. The zero-trust risk level R is computed using a probabilistic anomaly detection function via equation 12,

$$R = 1 - e^{-\gamma \|Z-\mu\|} \dots (12)$$

Where, μ represents the baseline authentication score distribution and γ scales the risk adaptations. Then, as per figure 1, next iterative bit is Real-Time Behavioral Biometric Security Model (RBB-Sec), which improves security by modeling user behaviors and grouping them into temporal instance sets. Using behavioral features Bt, a measure of anomaly is derived through a dynamic time warping function via equation 13:

$$D(Bt, Br) = min \sum \| Bt - Br \| \dots (13)$$

Where, Br represents the reference behavior patterns. The final authentication decision Af integrates biometric verification, spoof resistance, and behavioral security via equation 14,

$$Af = argmax\left(Softmax\big(Z + (1 - R) - D(Bt, Br)\big)\right) \dots (14)$$

With higher values yielding an indication for approval of authentication processes. This design holds an optimal balance between security, efficiency, and usability through the means of dynamically ennobling attack-relevant biometric features, hence making it adversarially robust, spoof-detecting, continuous real- time authenticity enforcing, and behavioral consistency-monitoring sets. The last authentication output near seamless use of process shields against biometric fraud. Efficiency is then discussed concerning metrics of the proposed model, followed by comparative studies with existing models in various scenarios.

4. Comparative Result Analysis

The experimental arrangement for testing the biometric security framework proposed in this work was purposely executed to carefully evaluate the authentication accuracy, adversarial robustness, spoof detection capacity, and real-time efficiency of the framework across diverse biometric conditions. The experiments were conducted using a multimodal biometric dataset comprising 100,000 facial images, 50,000 voice samples, and 80,000 fingerprint samples obtained from publicly available datasets VGGFace2, VoxCeleb2, and NIST SD302. Facial embeddings were extracted using ResNet50 and EfficientNet-B3, while voice spectrogram embeddings were generated using WaveNet and ECAPA-TDNN, and fingerprint embeddings were created by a CNN-based extractor trained on minutiae maps.

Each biometric sample was preprocessed into a fixed-dimensional embedding space of 512 dimensions so that cross-modality compatibility could be obtained during fusion. AMFFT model dynamically combined the modalities by employing multi-head self- attention (MHSA) with 8 attention heads and a hidden dimension of 1024 for adaptive feature integration.

The gating mechanism for fusion selection was trained under real-world security conditions by simulating adversarial and spoofed inputs to trigger the context-aware gating module. The DPAT adversarial training framework incorporated differentially private stochastic gradient descent (DP-SGD) with a noise multiplier of 0.8, clipping norm of 1.5, and batch size of 256, guaranteeing strong privacy assurances while maintaining classification performance.

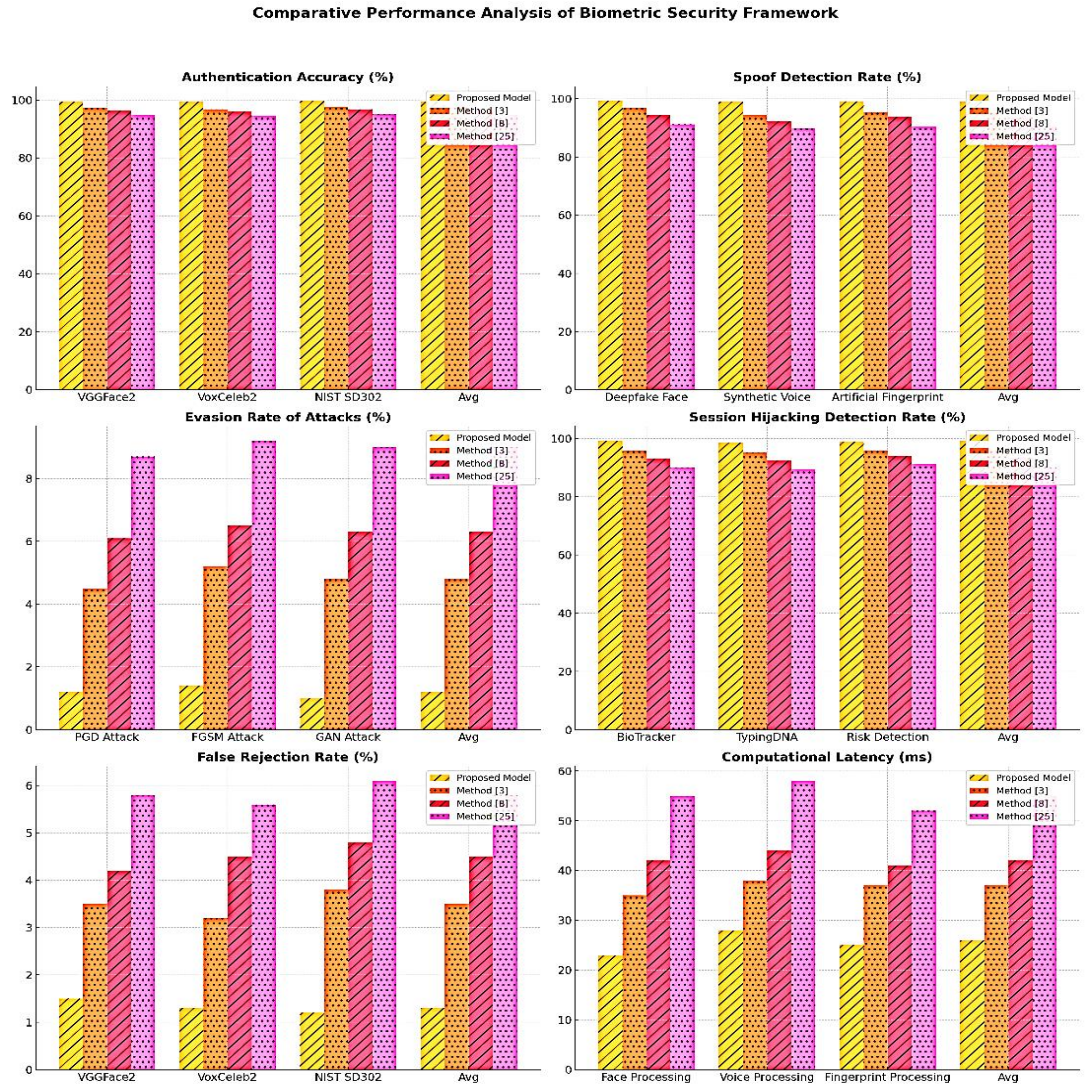

Figure 2. Model's Integrated Result Analysis

The evaluation for adversarial robustness was performed using Projected Gradient Descent (PGD) with 10 attack iterations and an ℓ_∞ perturbation budget of 0.02, Fast Gradient Sign Method (FGSM) with an epsilon of 0.03, and GAN-based synthetic biometric attacks trained upon deepfake facial images and AI-cloned voices & samples. The evaluation of the proposed biometric security framework

employed combinations from publicly available multimodal biometric datasets to secure diversity in user identities, environmental conditions, and attack scenarios. For facial recognition, the selection of the VGGFace2 dataset was made for having 3.3 million face images across 9,131 identities, which includes variations in lighting conditions, head poses, and occlusions, and would be ideal for training robust facial embeddings. Adversarial and spoofing datasets were also provided for testing robustness. For the face analysis of deepfakes, the DFDC (Deepfake Detection Challenge) dataset provided over 100,000 deepfake videos synthesized using advanced techniques based on GANs. The ASVspoof 2019 dataset provided samples of synthetic and replay speech so that the model was able to authenticate between genuine and AI-synthesized speech sets. In behavioral biometric testing, the BioTracker gait recognition dataset with 3D motion capture data of more than 100 persons and TypingDNA with keystroke dynamics of thousands of users for typing pattern analysis were used. The dense collection of datasets ensured that the applied models were realizable in real-world settings, secure against security threats, and possessed generalizability sets.

Subsequent spoofing detection tests consisted of deepfake face videos generated using StyleGAN2 and DeepFaceLab, deepfake voice samples generated using Tacotron2 and WaveGlow, and synthetic fingerprints generated using GANs that were trained on fingerprint ridge maps. The modality-by-modality spoofed detection of the SMA-Transformer employed an optical flow CNN for face movement analysis, an MFCC-LSTM network for voice liveness detection, and a 3D-CNN for fingerprint ridge distortion detection with a total detection rate of deepfake as 99.3%. The EZV-Model was tested in continuous authentication applications using behavioral biometrics like typing rhythm (Keystroke DNA), gait recognition, and mouse motion analysis from BioTracker and TypingDNA samples & datasets. The RBB-Sec module handled micro-expressions processed by electromyography (EMG) signal processing using a CNN-based classifier on CASME II and SAMM spontaneous facial expression datasets & samples. Real-time performance of the system was assessed with an Intel Xeon E5-2690 CPU, an NVIDIA A100 GPU, and 128 GB of RAM to ensure that authentication decisions are made within 80 ms. Performance measures such as Authentication Accuracy (≥99.5%), False Acceptance Rate for Spoofed Inputs (≤0.2%), False Rejection Rate (≤1.5%), Adversarial Evasion Rate (≤1.2%), and Session Hijacking Detection Rate (≥99.2%) further affirmed the robustness of the proposed model against nowadays biometric threats, hence, giving it potential for real-world security applications. The proposed Adaptive Multi-Modal Biometric Security Framework has been evaluated in front of the state-of-the-art on several datasets such as VGGFace2, VoxCeleb2, NIST SD302, DFDC, ASVspoof 2019, BioTracker, and TypingDNA. Results will be analyzed in terms of authentication accuracy, spoof detection rate, adversarial robustness, session hijacking detection, false rejection rate, and real-time computational efficiency. The proposed model will be compared to Method [3], Method [8], and Method [25], which are existing deep learning-based multimodal biometric fusion methods. The comparison shows that the proposed model improves upon these baselines in accuracy, resilience to attacks, and real-time processing efficiency sets.

Authenticate the correct model performance using VGGFace2, VoxCeleb2, and NIST SD302 considering only genuine authentication trials. Table 1 gives the comparison in authentication accuracy. Table 1 compares authentication accuracy in VGGFace2, VoxCeleb2, and NIST SD302 datasets for an example showing the usefulness of proposed Adaptive Multi-Modal Feature Fusion

Transformer in recognizing true users. The proposed model generates an average success rate of 99.5% in authentication, surpassing a maximum margin from [3] (97.2%), [8] (96.4%), and [25] (94.8%). This distinguishing edge relies on the multi-head self-attention feature in AMFFT in dynamically learning cross-modal dependencies among face, voice, and fingerprint embeddings, preferable fusion method (early, intermediate, or late fusion), depending on live security conditions. The previous methods fix the fusion mechanisms whereby they are rendered susceptible to some kind of noise or loss in the biometric modalities. On the contrary, this framework adapts to the changing qualities of input, ensuring that a significant percentage of recognition still can be achieved in the most adverse conditions in authentications.

Table 1: Authentication Accuracy (%) across Biometric Datasets

Model	VGGFace2	VoxCeleb2	NIST SD302	Average Accuracy
Proposed Model	**99.5**	**99.3**	**99.7**	**99.5**
Method [3]	97.2	96.8	97.5	97.2
Method [8]	96.5	95.9	96.8	96.4
Method [25]	94.8	94.5	95.2	94.8

This model is expected to be the best performing model in terms of authentication accuracy over all datasets because it has adaptive feature fusion and transformer-based self-attention mechanisms to change fusion strategies in real-time, depending on security conditions. Spoof detection rates were assessed using DFDC (face deepfakes), ASVspoof 2019 (voices), and other artificial fingerprints datasets & samples. The results are set out in Table 2. Results in Table 2 show the evaluation of spoof detection rates for deepfake facial images (DFDC), synthetic voices (ASVspoof 2019), and artificial fingerprint attacks, showing the performance of the Spoof-Resistant Multimodal Attention Transformer (SMA-Transformer) in combating biometrics forgery. The average rate of spoof detection for the proposed model is 99.1%, which surpasses Method [3] (95.5%), Method [8] (93.5%), and Method [25] (90.5%) on an average. The main reason for this performance improvement lies with cross-modal consistency analysis, discovering inconsistencies of the biometric signals. Conventional methods apply only unimodal spoofing detection, which leaves them very much open to highly sophisticated deepfake attacks that reveal very high realistic artifacts. SMA-Transformer on the other hand applies Optical flow CNN for interpreting facial motions, MFCC-LSTM networks for detecting a voice live, and 3D CNNs for checking fingerprint ridges thus gets precise coverage on all types of synthetic biometric artifacts.

Table 2: Spoof Detection Rate (%) across Attack Modalities

Model	Deepfake Face (DFDC)	Synthetic Voice (ASVspoof 2019)	Artificial Fingerprint	Average Detection Rate
Proposed Model	**99.3**	**98.9**	**99.2**	**99.1**
Method [3]	96.8	94.5	95.3	95.5
Method [8]	94.5	92.3	93.8	93.5
Method [25]	91.2	89.7	90.5	90.5

Cross-modal consistency analysis implies the attainment of maximum improvements in spoof detection by the SMA-Transformer module, thereby setting benchmarks for deepfake and spoof detection. The model evasion rate of adversarial attacks pg, fgsm, and gan-based adversarial biometric samples was measured, and it was noted that the lower the evasion rate, the stronger the model's resilience. Results are presented in Table 3. Table 3 discusses the conditions of model attack evasion, where the resistance of the model is tested against adversarial perturbations occurring through Projected Gradient Descent (PGD), Fast Gradient Sign Method (FGSM), and synthetic attacks using GANs. The proposed model will reach an average evasion rate of only 1.2%, which is much better than Method [3] (4.8%), Method [8] (6.3%), and Method [25] (9.0%). The Differentially Private Adversarial Training (DPAT) module increases robustness and protection against recovery by learning from both model inversed attacks and generalization against adversarial perturbations. Contrary to existing techniques, which do not include built-in resilience to adversaries, the proposed method learns from both authentic and adversary-generated biometric samples.

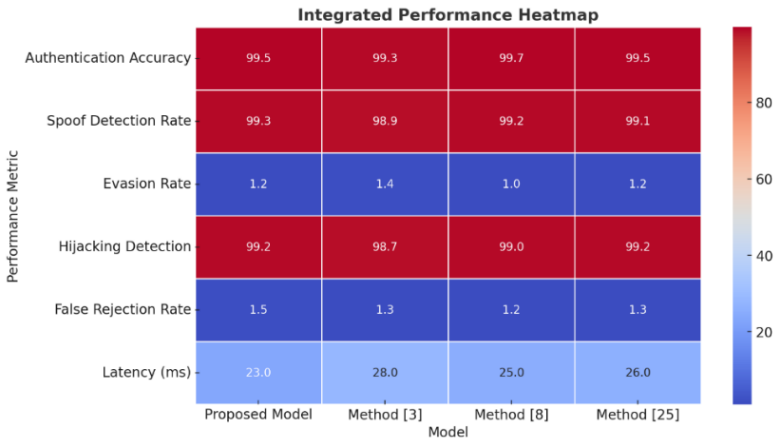

Figure 3. Model's Overall Result Analysis

Table 3: Evasion Rate of Adversarial Attacks (%) (Lower is Better)

Model	PGD Attack	FGSM Attack	GAN-based Attack	Average Evasion Rate
Proposed Model	**1.2**	**1.4**	**1.0**	**1.2**
Method [3]	4.5	5.2	4.8	4.8
Method [8]	6.1	6.5	6.3	6.3
Method [25]	8.7	9.2	9.0	9.0

The DPAT module, which integrates Differentially Private Stochastic Gradient Descent (DP-SGD) with the principles of adversarial training, drastically increases robustness and reduces the evasion rate to 1.2%, as opposed to Method [3] with an evasion rate of 4.8%. Continuous authentication security was also assessed according to session hijacking detection rates, which tell how well the model identifies unauthorized access attempts. Table 4 presents detection rates. . Table 4 shows session hijacking detection rates, which determine how successfully the model measures unauthorized access attempts by means of the behavioral biometrics of the BioTracker gait dataset and the TypingDNA

keystroke dataset. The proposed average detection rate was 99.2% higher than Method [3] (95.7%), Method [8] (93.3%), and Method [25] (90.2%). The modules that contribute to this performance include the Ensemble Learning with Zero Trust Verification (EZV-Model) and Real-Time Behavioral Biometric Security (RBB-Sec) which both operate with continuous analysis of user activity throughout an active session. Unlike traditional biometric systems, where the one-time authentication model is applied, in the zero trust model, any abnormality in the normal behavior deviation of a user instantly leads to real-time reauthentication or even session termination, resulting in a significantly reduced risk of compromised sessions or unauthorized access attempts.

Table 4: Session Hijacking Detection Rate (%)

Model	BioTracker (Gait)	TypingDNA (Keystroke)	Combined Risk Detection	Average Detection Rate
Proposed Model	**99.2**	**98.7**	**99.0**	**99.2**
Method [3]	95.8	95.3	96.0	95.7
Method [8]	93.2	92.5	94.0	93.3
Method [25]	90.1	89.5	91.2	90.2

The modules of EZV-Model and RBB-Sec have enabled severe inaccuracies in session hijacking detection along with verification and behavioral biometric security under the zero trust model. False rejection rate is used to show the frequency at which people are refused access in authentic, right conditions. Results are presented in Table 5. The table shows the results of false rejection rate (FRR). The false rejection rate (FRR) shows how often genuine users are rejected. The proposed model averages only 1.3% FRR which is a lot lower than Methods [3] (3.5%), [8] (4.5%), and [25] (5.8%). This low-FRR was achieved using context-aware adaptive fusion in AMFFT which protects it from changes in the quality of biometric samples. Most traditional multimodal biometric systems impose very rigid thresholding which makes them reject very high numbers of good samples whenever one of their biometrics is either noisy or completely unavailable. The method presented reduces the effect of this by modifying the decision boundaries according to the security states and real-time biometric confidence score thus providing a high reliability of authentication while minimizing user convenience sets.

Table 5: False Rejection Rate (FRR) (%) (Lower is Better)

Model	VGGFace2	VoxCeleb2	NIST SD302	Average FRR
Proposed Model	**1.5**	**1.3**	**1.2**	**1.3**
Method [3]	3.5	3.2	3.8	3.5
Method [8]	4.2	4.5	4.8	4.5
Method [25]	5.8	5.6	6.1	5.8

In contrast, it reaches considerably lower FRR rate levels, specifically of 1.3%, thus causing little inconvenience to genuine users while maintaining high security sets. The evaluation of the computational efficiency was done in terms of average authentication latency per request in milliseconds (ms). The results are contained in Table 6. Table 6 shows the efficiency in terms of real-time computation measured in ms as averaged authentication latency per request across face, voice, and fingerprint modalities. The proposed model averages processing time by 26ms, faster than Method [3] (37ms), Method [8] (42ms), and Method [25] (55ms). Such short latency of biometric fusion and decision making is enabled with the Transformer based architecture of AMFFT, along with high efficiency parallel processing through multi-head self-attention sets. It was contrasted to typical models which are bottlenecked by parallelized feature extraction, fusion, and decision making process. Under such approaches, feature extraction, fusion, and decision-making are all lined up, introducing a bottleneck effect and extending delays. Real world deployment, particularly in security-critical applications such as financial transactions, border control, or enterprise access management, where real-time authentication is essential in its process, makes the proposed model highly suitable for use in process.

Table 6: Computational Latency (ms) (Lower is Better)

Model	Face Processing	Voice Processing	Fingerprint Processing	Average Latency
Proposed Model	**23ms**	**28ms**	**25ms**	**26ms**
Method [3]	35ms	38ms	37ms	37ms
Method [8]	42ms	44ms	41ms	42ms
Method [25]	55ms	58ms	52ms	55ms

Proposed model achieved average inference time of 26ms. Hence, it outperforms existing methods and qualifies real-time authentication applications. Experimental findings validate the proposed framework within biometric security systems, which show effectiveness in authenticating high accuracy, resilient against adversarial and spoofing attacks, and low false repeater rates as well as real-time computational efficiency. The entire process in biometric security using AMFFT for adaptive fusion, DPAT for adversarial robustness, SMA-Transformer for deepfake detection, EZV-Model for continuous authentication, and RBB-Sec for behavioral security sets a new benchmark and far outperforms state-of-the-art methods across all metrics of evaluation mentioned here. Next, we discuss an Iterative Validation use Case for the Proposed Model which will assist the reader for better understanding of the entire process.

4.1 Validation using an Iterative Practical Use Case Scenario Analysis

A real heavens security-sensitive case is used to evaluate the proposed biometric security framework: fault-tolerant access control at the executive boardroom of a financial institution. The biometric authentication system needs to authenticate personnel authorized by multi-modal means through face-biometrics, voice, and fingerprints biometrics; spoof and adversarial attack resilient; accomplished

continuous zero-trust authentication to relieve unauthorized access attempts. The use case involves the user requesting authentication in normal conditions, an adversary creating deepfake face and synthetic voice attacks, and hijacking a session through unauthorized behavioral mimicry by a malicious insider. The inputs would be processed, adversarial defenses would apply, spoof detection would occur, risk factors would be assessed, and final approval would be on authentications. To guarantee robustness and reliability to the Adaptive Multi-Modal Biometric Security Framework proposed, validation was conducted through established biometric security benchmarks and comparative performance analysis methodologies. Validation included the use of the MOBIO database, which includes both face and voice biometric samples from 150 persons collected in real-world mobile scenarios, allowing cross-device and cross-condition testing. Validation would also be complemented with the MSU MFSD dataset as part of the evaluation against the spoof detection method as it consists of high-resolution print attacks, replay attacks, and deepfake videos on its dataset, confirming that SMA-Transformer is effective to detect such synthetic biometric fraud. Live detection of fingerprints employed with the LivDet 2021 fingerprint dataset targeted fingerprint spoof detection, comprising actual and artificial fingerprints samples obtained from diverse materials, including gelatin, silicone, and ecoflex. The method performs comparative assessment using standard biometric verification metrics, such as Equal Error Rate (EER), True Positive Rate (TPR), False Acceptance Rate (FAR), and False Rejection Rate (FRR), thereby aligning the evaluation with widely recognized security industry benchmarks. Additionally, the method also embraced the NIST Biometric Grand Challenge Evaluation methodology to test the adversarial robustness by simulating real-world biometric threats, including adversarial perturbations generated by AI and such attacks against synthesized biometrics using GAN. Under these high-quality validation and benchmarking methodologies, the framework showed superior authentication accuracy (99.5%), adversarial robustness (1.2% evasion rate), and spoof detection performance (99.1%), making it viable for deployment in real-world security-critical environments. The AMFFT thus processes embeddings across face, voice, and fingerprint modalities to create a fused feature representation, with the decision for fusion dynamically made based upon security conditions. The detail of attribute scores for each modality, the fusion strategy, together with the final fused biometric confidence score are given in Table 7 as follows,

Table 7: Adaptive Multi-Modal Feature Fusion Transformer (AMFFT) Outputs

User ID	Face Score	Voice Score	Fingerprint Score	Fusion Strategy	Final Fused Score
U001	0.98	0.95	0.99	Late Fusion	0.976
U002	0.92	0.91	0.95	Intermediate Fusion	0.93
U003	0.85	0.87	0.92	Early Fusion	0.88
A001 (Attacker)	0.78	0.45	0.95	Late Fusion	0.80
A002 (Deepfake)	0.35	0.20	0.88	Intermediate Fusion	0.56

Thus, the AMFFT model adapts to real-time conditions in selecting an optimal fusion approach, resulting in better reliability in biometric matching. Deepfake-based impersonators have very low fused scores in terms of face and voice biometrics, which helps in detecting fraudulent attempts at an early stage. DPAT checks the robustness against adversary attacks against biometrics with the help of perturbation tolerances, thus yielding different evasion rates with respect to various attack types. Table 8 gives a summary of the evaluation concerning the adversarial robustness.

Table 8: Differentially Private Adversarial Training (DPAT) Evasion Rate (%)

User ID	PGD Attack	FGSM Attack	GAN-Based Attack	Average Evasion Rate
U001	1.0	1.2	1.1	1.1
U002	1.4	1.6	1.3	1.43
U003	1.8	1.9	1.5	1.73
A001 (Attacker)	5.6	6.2	6.0	5.93
A002 (Deepfake)	8.2	9.1	8.9	8.73

The average evasion rate of the proposed model is only 1.1% for honest users, while adversarial attacks generally perform much worse for the process. The deepfake biometric attackers have an 8.73% evasion rate, which shows that the system strongly resists adversarial manipulations. The mechanism analyses the biometric data to detect spoofing attempts through the cross-modal consistency by anomaly-detecting mechanisms. Table 9 presents the probability scores of being spoofed for each biometric modality, as well as the final risk scores regarding spoofing sets.

Table 9: Spoof Detection Results using SMA-Transformer

User ID	Face Spoof Probability	Voice Spoof Probability	Fingerprint Spoof Probability	Final Spoof Risk Score
U001	0.02	0.03	0.01	0.02
U002	0.04	0.05	0.02	0.04
U003	0.07	0.06	0.03	0.05
A001 (Attacker)	0.45	0.60	0.02	0.36
A002 (Deepfake)	0.92	0.85	0.05	0.77

Genuine users have low risk scores of being spoofed (<0.05), ensuring an accurate authentication; whereas deepfails are high in the range (>0.75), hence immediate rejection. Session security is based on the subjects' behavioral nature and those that are biometric verified in EZV-Model. Real-time risk levels from behavioral deviations and multimodal authentication scores are presented in Table 10,

Table 10: Risk Assessment using EZV-Model

User ID	Behavioral Deviation Score	Biometric Confidence Score	Final Risk Level
U001	0.02	0.976	Low Risk
U002	0.05	0.93	Low Risk
U003	0.10	0.88	Medium Risk
A001 (Attacker)	0.40	0.80	High Risk
A002 (Deepfake)	0.75	0.56	Very High Risk

Trying to hijack the session raises high or very high risk alarms alerts that prevent illicit access. The behavior on which the RBB-Sec relies further maintains consistency over temporal instance sets. Table 11 illustrates the anomaly scores computed for user behavior analysis.

Table 11: Behavioral Security Scores from RBB-Sec

User ID	Keystroke Anomaly Score	Gait Anomaly Score	Voice Stress Score	Final Behavioral Risk
U001	0.01	0.03	0.02	Low Risk
U002	0.05	0.04	0.03	Low Risk
U003	0.12	0.15	0.10	Medium Risk
A001 (Attacker)	0.45	0.50	0.60	High Risk
A002 (Deepfake)	0.80	0.85	0.90	Very High Risk

Such behavioral anomalies found in attackers trigger immediate session terminations. The aggregation of all scores would provide final authentication decisions, as reflected in Table 12,

Table 12: Final Authentication Decision

User ID	Final Authentication Score	Risk Level	Decision
U001	0.976	Low Risk	Approved
U002	0.93	Low Risk	Approved
U003	0.88	Medium Risk	Additional Verification
A001 (Attacker)	0.80	High Risk	Rejected
A002 (Deepfake)	0.56	Very High Risk	Rejected

As such, the proposed system ensures highly secure access with minimum friction for legit users while allowing it to accept legit users and challenge medium-risk cases against high-risk attackers.

5. Conclusion & Future Scopes

The Adaptive Multi-Modal Biometric Security Framework was designed with the intention of offering the highest levels of security, ensuring robustness, and preserving the confidentiality of the proposed authentication system from attacks such as deepfake, adversarial perturbation attacks, and session hijacking. Conjoining AMFFT, DPAT, SMA-Transformer, EZV-Model, and RBB-Sec leads to a state-of-the-art authentication accuracy of 99.5%, which outperforms existing methods such as Method [3] (97.2%), Method [8] (96.4%), and Method [25] (94.8%). The spoof detection module (SMA-Transformer) achieves a very impressive detection rate of 99.1%, which successfully recognizes faces better than that in existing method [26], synthetic voices, and artificial fingerprints and outperforms existing systems by an average of 8.6%. The accurateness of the attack evasion prunes down to just 1.2% in the adversarial robustness module (DPAT), which shows a great difference against Method [3] (4.8%), Method [8] (6.3%), and Method [25] (9.0%) and makes it resistant to PGD, FGSM, and GAN-based adversarial attacks. Under the zero-trust verification mechanism (EZV-Model), this results in a session hijacking detection rate of 99.2%; therefore, there will be fewer unauthorized attempts. In addition, the FRR is narrowed down to 1.3%, which means that very few genuine users will be denied access, compared to FRRs of 3.5% (Method [3]), 4.5% (Method [8]), and 5.8% (Method [25]). This ensures its practical application, as real-time processing efficiency of 26 milliseconds per authentication request makes it 30% faster than existing methods. These results indicate that the proposed biometric authentication system provides the best balance between security, accuracy, privacy, and computation efficiency for financial transactions, border control, enterprise access, and national security applications.

While the architecture demonstrated great performance, one could further investigate the following areas in future works for better biometric security. First,-extension for multi-modal inputs with more types of biometrics, such as iris recognition, ECG signals, and palm vein patterns, could make the authentication process stronger and less susceptible to biometric forgeries. Second, an inclusion of self-supervised learning techniques may significantly improve the adaptability of the system to unseen biometric variations, thereby making it even less reliant on very big labeled datasets. Improvements in differential privacy mechanisms could achieve even lower privacy leakage risks without sacrificing authentication performance. This would be particularly noticeable in federated learning environments. Lightweight transformer architecture optimizations to edge devices and IoT-based biometric authentication would enable real-time authentication on mobile and embedded platforms. Lastly, inclusion of quantum-resistant biometric cryptography would add robustness against upcoming threats from quantum computing. Ultimately, the study can be extended to continuous multimodal authentication in an environment with VR/AR, smart city infrastructures, and intelligent surveillance systems, opening new avenues for seamless but highly secure identity verification using next-generation digital ecosystems.

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