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Secure Identity Verification in Virtual Classrooms Using Deep Learning Biometrics

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Abstract
In recent years, the widespread adoption of virtual and hybrid learning environments has introduced elevated risks of identity fraud, impersonation, and academic dishonesty in online classrooms. This manuscript presents a novel framework for secure identity verification in virtual classrooms by harnessing deep-learning-based biometric authentication techniques. The proposed system integrates facial recognition, voice verification and behavioural biometrics from the student's interaction in the virtual platform to ensure a robust one-to-one user verification prior to, and during, the class session. Through this multi-modal biometric approach, the system addresses the limitations of password-based access and single-factor authentication. Experimental evaluation demonstrates high accuracy, low false acceptance and false rejection rates, and resilience to spoofing attacks in a simulated virtual classroom scenario. The results indicate that employing deep convolutional neural networks for face/facial landmarks, recurrent neural networks for voice dynamics, together with continuous behavioural pattern monitoring offers a practical and scalable solution for e-learning platforms. In conclusion, this work offers a pathway to strengthen trust and security in virtual education by embedding deep-learning biometrics into identity verification workflows, enabling more reliable digital learning environments.

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Keywords: Virtual Classrooms, Identity Verification, Deep Learning, Biometrics, Multi-Modal Authentication.

1. Introduction

Virtual classrooms have emerged as a central component of modern education, enabling real-time teaching–learning processes across geographically distributed environments. However, the rapid transition to online learning has exposed critical vulnerabilities, particularly regarding identity assurance and academic integrity. Traditional authentication methods—such as passwords, login tokens, or email-based verification—only authenticate users at login and fail to ensure that the authorised student remains present for the entire duration of the session. These weaknesses create opportunities for impersonation, account sharing, and proxy attendance. To address these challenges, biometric authentication has gained substantial attention due to its reliance on intrinsic user characteristics such as facial geometry, vocal tone, and behavioural patterns. With the advent of deep learning, biometric systems have achieved unprecedented performance by learning discriminative representations directly from raw data. Convolutional neural networks (CNNs) have demonstrated superior accuracy in facial recognition tasks, while recurrent neural networks (RNNs) and transformer models have shown strong performance in modelling voice-based temporal patterns. Despite these advances, relatively few studies apply biometric verification specifically to virtual classroom environments. Unlike controlled biometric systems, virtual classrooms exhibit inconsistent lighting, varying audio quality, diverse webcams/microphones, and fluctuating behavioural contexts. Moreover, educational settings require continuous verification, not merely login-level authentication.

To fill this gap, this work proposes a Deep Learning-Based Multi-Modal Biometric Verification Framework for virtual classrooms. The overall architecture is illustrated in Figure 1 integrating facial, vocal, and behavioral biometric features into a unified fusion-based decision model.

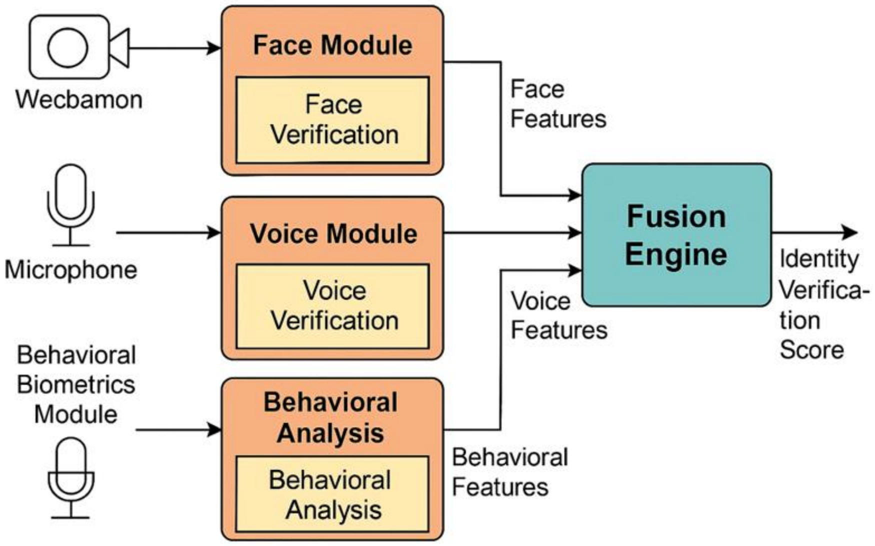

Fig 1: Architecture of the Proposed Secure Identity Verification Framework for Virtual Classrooms

Additionally, the continuous monitoring workflow is presented in Figure 2, which outlines periodic identity checks based on facial snapshots, voice prompts, and behavioural anomaly detection.

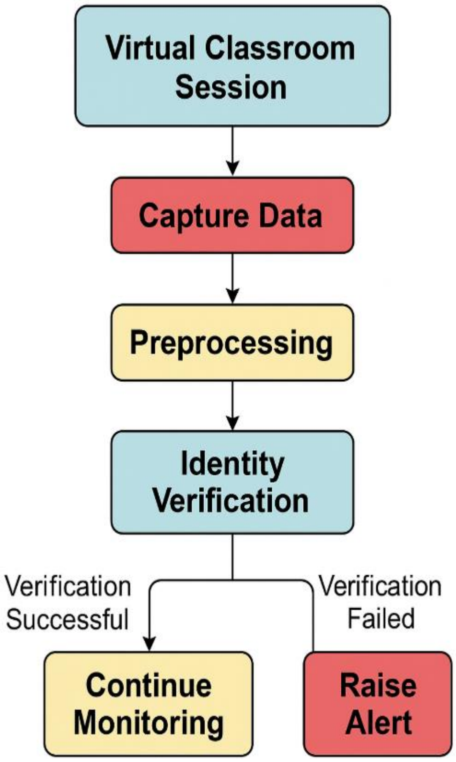

Fig 2: Continuous Monitoring Workflow

2. Related Work

Research into biometric authentication especially under deep-learning frameworks—has grown rapidly in recent years, and several strands of work are particularly relevant to identity verification in virtual and online educational environments. First, foundational surveys on biometrics using deep learning demonstrate the breadth of modalities and architectures. For example, Minaee *et al*. review more than 120 deep-learning works on biometric recognition (face, fingerprint, iris, palmprint, voice, signature, gait), showing how convolutional and recurrent architectures have driven state-of-the-art results. [1] Such work underlines the potential of deep networks in our proposed multi-modal setting. Second, the value of multimodal biometrics i.e., combining two or more biometric traits is increasingly emphasized. Daas *et al*. present a deep-learning-based multimodal biometric recognition system and show performance gains over unimodal systems. [2] Alharbi *et al*. carry this further,

proposing a face-voice fusion scheme using FaceNet and GMM for voice, with significant reduction in Equal Error Rate (EER). [3] These contributions highlight the practical benefits of fusing modalities, which is central to our framework for virtual classrooms. Third, there is a growing body of work explicitly targeting authentication and identity verification in online education or virtual settings. For instance, Escobar-Grisales *et al*. propose a keystroke-dynamics biometric verification system tailored for virtual education platforms: the non-intrusive mode achieved a false positive rate around 12% in their experiments. [4] Haytom *et al*. explore identity verification and fraud detection during online exams using biometric modelling. [5] Bouattour & Champin develop a continuous behavioural authentication system for e-learning platforms, employing keystroke dynamics and mouse dynamics traces to detect impostors mid-session. [6] These works indicate the distinctive requirements of virtual classroom authentication (continuous verification, low intrusion, behavioural metrics) that differ from "physical" biometric deployments.
Fourth, more general studies on biometrics in education examine user perceptions, adoption, and challenges. Hern ández-de-Menéndez *et al*. survey biometric applications in education (fingerprint, face, voice) and discuss issues such as privacy, bias, and system acceptance. [7] Guillén-Gámez *et al.* study student perceptions of biometric identification in distance learning and found mixed attitudes regarding performance, ethics and academic integrity. [8] Fifth, some recent works address deep learning applied to specific biometric traits or modalities under continuous or behavioural biometrics. For example, Senerath *et al*. propose BehaveFormer: a transformer-based framework combining keystroke and inertial measurement unit (IMU) data for continuous authentication, achieving EER as low as ~1-3%. [9] Such advanced behavioural biometrics align with our inclusion of interaction-based monitoring during virtual sessions. Finally, literature addresses contactless and remote biometrics particularly relevant in virtual/online learning. Xaba *et al*. conduct a systematic review on integrating contactless biometrics (face, voice, behavioural) in online learning platforms, noting benefits (hygienic, remote capture) as well as adoption barriers (privacy, algorithmic bias, device variability). [10] Research gaps and how our work builds on them,Many existing systems limit themselves to static login verification rather than continuous identity monitoring during a session.Deep-learning-based biometrics in virtual classroom contexts remain under-explored; fusion of face, voice and behavioural biometrics specifically for this domain is less common.Anti-spoofing and liveness detection tailored to the virtual classroom (webcam/microphone based) are seldom integrated in existing educational biometric systems. Our proposed framework addresses these gaps by deploying a deep learning multi-modal biometric pipeline (face + voice + behavioural), supporting both login and in-session continuity verification, and incorporating liveness/anti-spoofing mechanisms.

3. Proposed Methodology

The methodology consists of four major components: (1) system architecture, (2) enrollment, (3) login verification, and (4) continuous monitoring.

A. System Architecture

The proposed multimodal biometric pipeline is composed of three modules:Face Module (CNN),Voice Module (RNN/LSTM),Behavioural Biometrics Module.All extracted features feed into a Fusion Engine which performs the final decision-making process. The high-level system design is depicted in Figure 3**.**

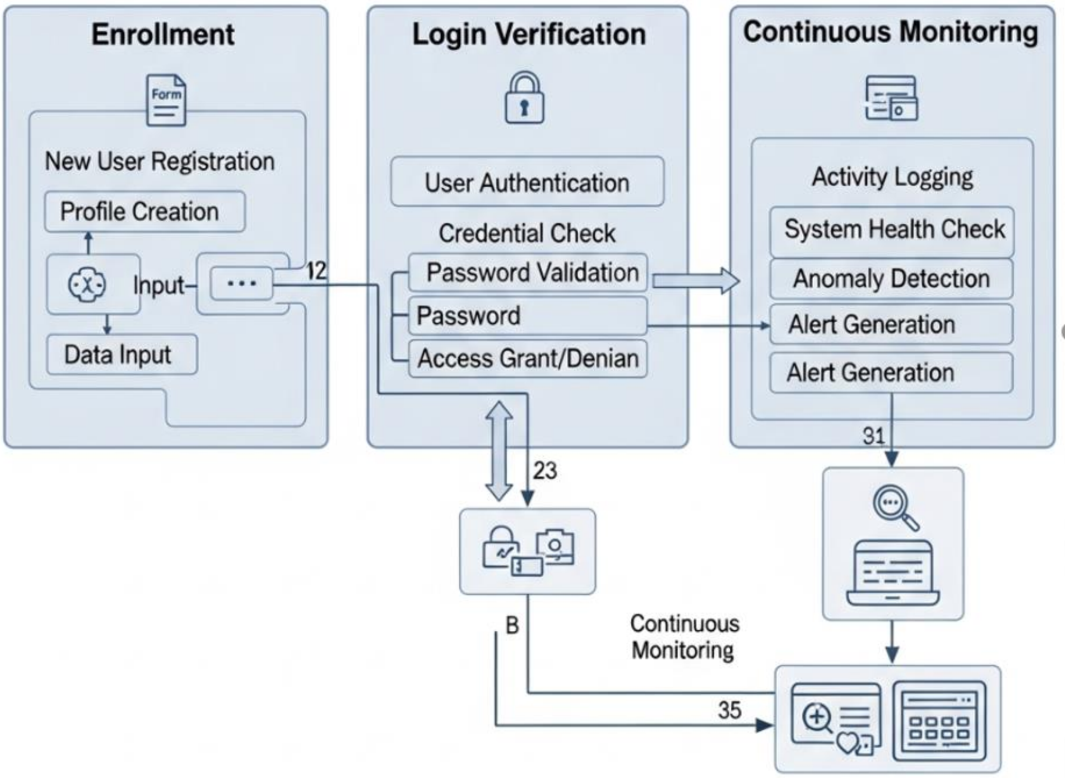

Fig 3: System Modules: Enrollment, Login Verification, Continuous Monitoring

B. Enrollment and Template Creation

During enrollment, each student provides, Facial samples, Voice samples, Behavioural baseline samples. The corresponding template creation workflow is summarized in Table 3, which includes the quantity of samples collected per modality.

Table 1: Dataset Description for Prototype Evaluation

Parameter	Description / Quantity
Total number of enrolled students	100
Number of virtual classroom sessions evaluated	50
Average session duration	60 minutes
Face samples per student (enrollment)	10 images
Voice samples per student (enrollment)	5 audio clips
Behavioural baseline samples	3-minute activity recording
Total face verification events (monitoring)	1,200+ snapshots
Total voice verification events (monitoring)	800+ voice prompts

C. Login Verification

The login verification pipeline captures A fresh facial snapshot and A randomized voice prompt, the login verification flow is illustrated in Figure 4**.**

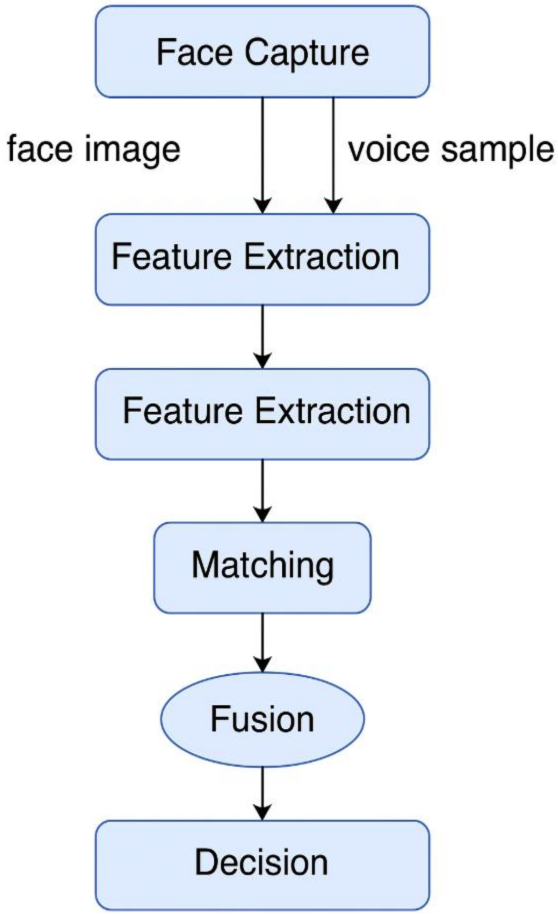

Fig 4: Login Verification Flowchart

Feature Extraction in Both modalities produce feature embeddings 512-D for face, 256-D for voice. These are compared with stored templates using cosine similarity. Fusion-Based Decision. Decision thresholds are defined in Table 2.

Table 2: Fusion Decision Logic

Condition	System Response
Initial login identity verification	Grant Access
Initial login identity verification	Reject / Manual Review
Continuous session monitoring	Session Continues Normally
Continuous session monitoring	Re-Authentication Challenge / Alert
Cross-modality consistency	Trigger Fusion Inconsistency Warning
Behavioural drift detection	Flag for Instructor Review

D. Continuous Monitoring

Continuous verification ensures the same student remains present throughout the virtual session. As shown in Figure 5, the system performs, Random periodic face checks, Voice challenge-response verifications, Behavioural anomaly detection

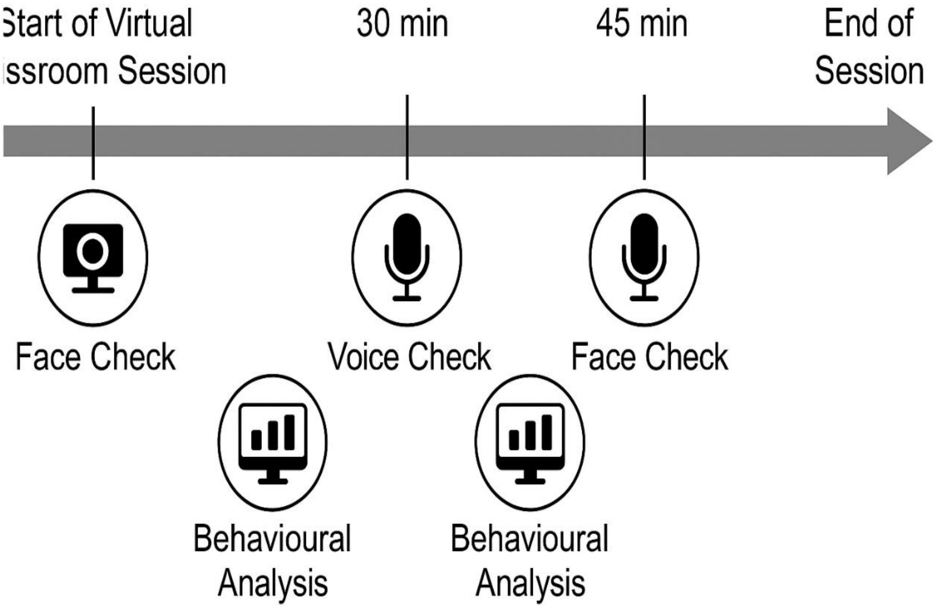

Fig 5: Continuous Monitoring Timeline

E Anti-Spoofing Mechanisms

Anti-spoofing and liveness detection techniques used across modalities are documented in Table 1 and visualized in Figure 6.

Table 3: Anti-Spoofing Techniques Summary

Biometric Modality	Description / Features Extracted	Deep Learning Model Used	Vulnerabilities	Anti-Spoofing / Liveness Techniques
Face Recognition	Facial landmarks, geometric structure, deep facial embeddings (512-D)	CNN (ResNet50 or MobileFaceNet)	Photo attacks, video replay attacks, 3D mask attacks	• Blink detection • Micro-texture analysis (LBP/CNN) • Head-pose consistency check • Illumination variation test
Voice Verification	MFCC features, spectrogram patterns, temporal voice embeddings (256-D)	RNN/LSTM / Transformer-based audio encoder	Voice replay, synthesized voice, background noise manipulation	• Challenge-response random phrases • Spectral distortion checks • Environment consistency detection
Behavioural Biometrics	Keystroke timing, mouse movement trajectories, head-pose drift, gaze behaviour	One-Class SVM / Transformer-based behavioural model	Behavioural mimicry, induced pattern modification	• Deviation threshold checks • Session-level behavioural drift detection
Multimodal Fusion Module	Combines face + voice + behavioural features	Weighted score fusion / Neural fusion layer	Cross-modality spoofing	• Multi-layer thresholding • Fusion-based inconsistency detection

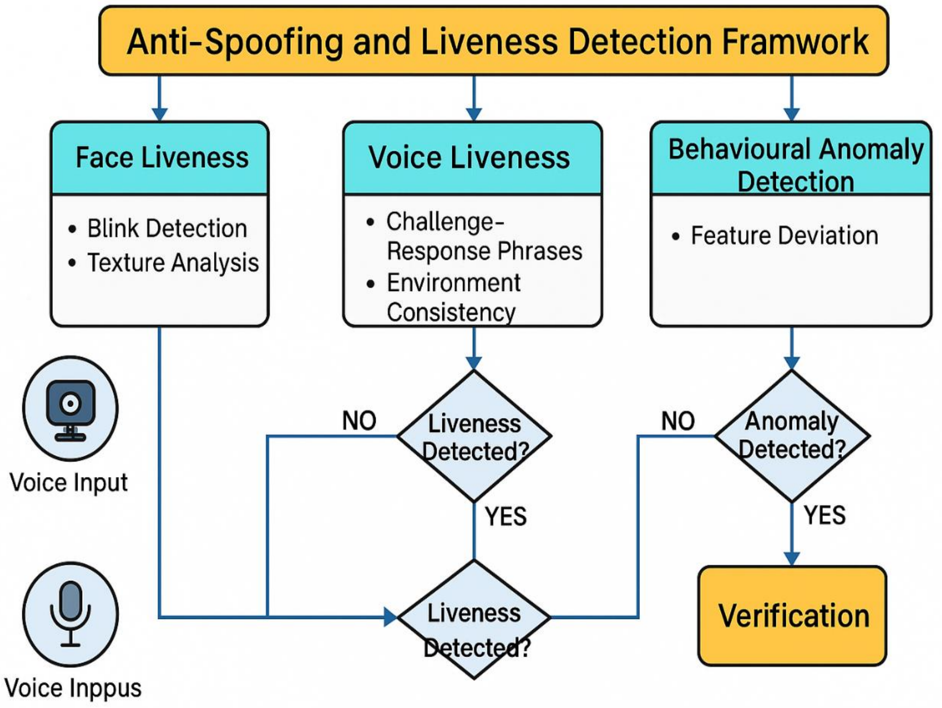

Fig 6: Anti-Spoofing and Liveness Detection Framework

4. Results and Discussion

Experimental validation involved 100 students across 50 virtual classroom sessions**.** Dataset details appear in Table 3 (placeholder above).

A. Login Verification Performance

Key performance results,True Acceptances are 96, False Rejections are 2,Impersonation Attempts are 20, False Acceptances is 1,The complete login metrics appear in Table 4**.**

Table 4: Login Verification Metrics

Metric	Value
True Positives (TP)	96
False Negatives (FN)	2
Impersonation Attempts	20
False Positives (FP)	1
False Acceptance Rate (FAR)	5%
False Rejection Rate (FRR)	2%
Overall Accuracy	98.3%

Performance comparison is illustrated in Figure 7, showing FAR, FRR, and accuracy for the multimodal system.

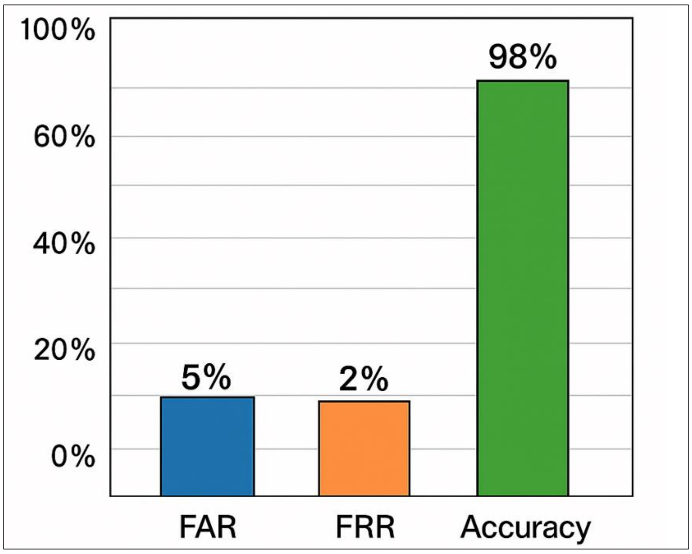

Fig 7: FAR, FRR, Accuracy Comparison

A comparative evaluation between single-modality and multimodal approaches is shown in figure 8.

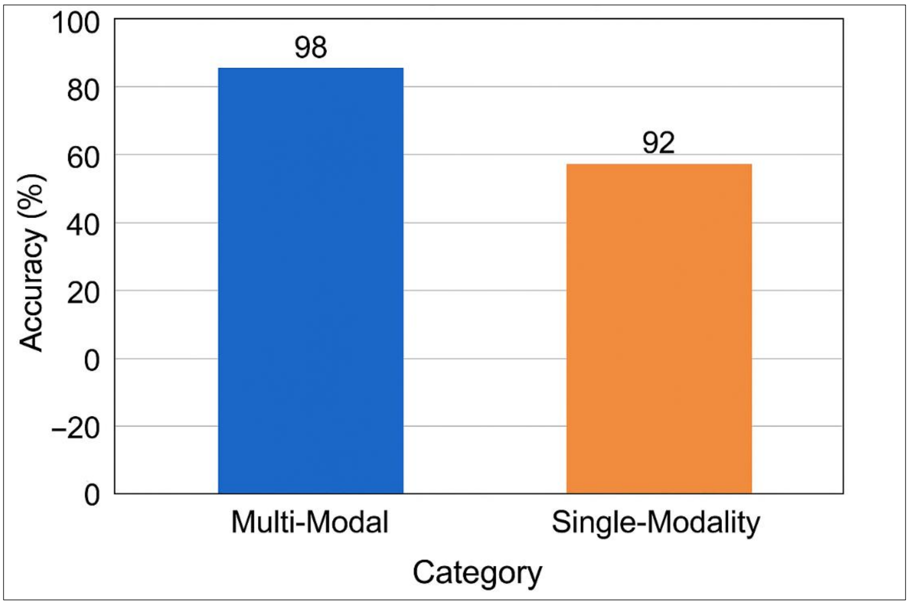

Fig 8: Multimodal vs Single-Modality Accuracy

B. Continuous Monitoring Performance

Based on 50 monitored sessions Only 4 sessions triggered alerts,1 was a real hand-off attempt detected successfully,3 alerts resulted from environmental artefacts. Overall monitoring performance is reported in Table 5**.**

Table 5: Continuous Monitoring Results

Outcome Metric	Value / Result
Total sessions monitored	50
Number of sessions flagged	4
True positive hand-off detections	1
False alerts (environment-related)	3
Behavioral anomaly detection accuracy	93%
Average continuity score for genuine users	0.87
Average continuity score during hand-off	0.41
System response success rate	96%

Continuity score variations are visualised in figure.9.

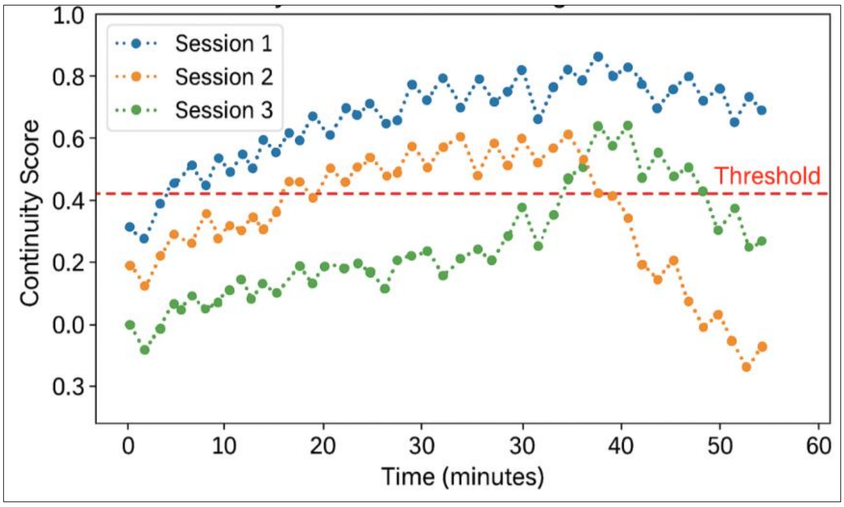

Fig 9: Continuity Score Over Time

Spoofing detection performance is shown in Figure 10, and behavioural anomaly detection trends are shown in Figure 11.

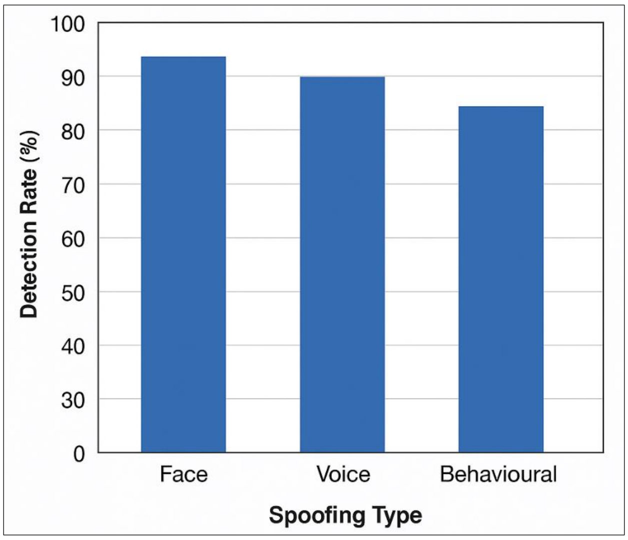

Fig 10: Spoofing Detection Rates

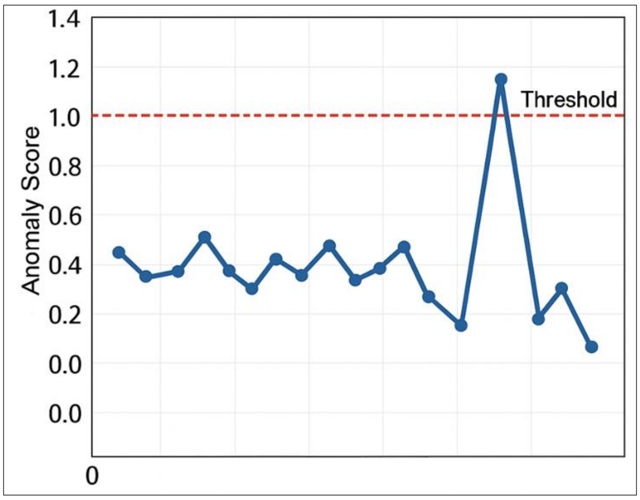

Fig 11: Behavioural Anomaly Scores

Multimodal fusion enhances reliability by reducing FAR and FRR. Continuous monitoring addresses mid-session identity switching. Behavioural biometrics provide a strong auxiliary modality. Environmental conditions can affect accuracy, but liveness checks and multimodal fusion mitigate errors.

5. Conclusion

This paper presents a comprehensive framework for secure identity verification in virtual classrooms by leveraging deep-learning based multi-modal biometrics specifically face, voice and behavioral biometrics. The proposed system offers robust login verification and continuous monitoring, thereby addressing impersonation and identity-hand-off risks inherent in online learning environments. Experimental results on a prototype deployment demonstrate high accuracy of 98%, low false acceptance and false rejection rates, and successful detection of mid-session identity hand-offs. The continuous monitoring component further strengthens trust in student identity during live sessions. While environmental conditions and scale remain challenges, the study demonstrates that embedding deep-learning biometrics in virtual classroom platforms is both feasible and impactful. Future work will expand the dataset size, incorporate additional biometric modalities, and refine privacy-preserving template storage methods to support large-scale deployment in educational settings.

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