LivePresence Attendance: Encrypted, Anti-Spoof and Liveness-Verified System

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Abstract

The increasing demand for secure, contactless, and automated attendance systems has led to significant research in biometric authentication technologies. However, traditional attendance systems suffer from limitations such as proxy attendance, spoofing attacks, and lack of secure audit mechanisms. This paper presents LivePresence Attendance, a real-time face recognition-based attendance system integrated with liveness detection, anti-spoofing mechanisms, and encrypted logging.

The system employs a multi-stage verification pipeline consisting of face detection, behavioral liveness verification using blink and head movement analysis, identity recognition through embedding comparison, and secure database storage. A challenge-based liveness mechanism ensures that only physically present users can authenticate, effectively preventing spoofing attacks using printed images, digital screens, or replayed videos.

Experimental evaluation under real-world conditions demonstrates a recognition accuracy of 92.8%, liveness verification success rate of 94.1%, and an average system latency of 320 ms, making the system suitable for real-time deployment. The system is implemented using Python, OpenCV, MediaPipe, and SQLite, with AES-based encryption ensuring data confidentiality.

The proposed system provides a secure, scalable, and practical solution for attendance management in academic and organizational environments.

Keywords: Face Recognition, Liveness Detection, Anti-Spoofing, Secure Systems, AES Encryption, Computer Vision

1. Introduction

Attendance management systems are essential in academic institutions and organizational environments for monitoring participation and ensuring accountability. Traditional methods such as manual registers and RFID-based systems are often inefficient, prone to human error, and vulnerable to proxy attendance. Although biometric systems such as fingerprint recognition have improved reliability, they introduce limitations including hygiene concerns, hardware dependency, and susceptibility to spoofing.

With the advancement of computer vision technologies, face recognition has emerged as a promising contactless alternative for attendance systems. It enables automated identification using standard camera devices without requiring physical interaction. However, most existing face recognition systems lack mechanisms to verify whether the detected face belongs to a live individual. This makes them vulnerable to presentation attacks, where unauthorized users attempt to deceive the system using photographs, videos, or digital displays.

To overcome these limitations, this paper proposes LivePresence Attendance: An Encrypted, Anti-Spoof and Liveness-Verified System, which integrates face recognition with behavioral liveness detection and secure data handling. The system introduces a challenge-based verification mechanism using eye blinking and head movement to ensure that only physically present users can authenticate.

In addition to improving authentication reliability, the system incorporates encrypted logging and administrative controls to enhance data security and system monitoring. The objective of this work is to develop a secure, real-time, and practical attendance solution that addresses both usability and security challenges in existing systems.

The rest of the paper is organized as follows: Section 2 presents the review of literature, followed by system architecture, methodology, implementation details, and experimental evaluation.

2. Review of Literature

Face recognition systems have evolved significantly over the past decade. Early approaches such as Eigenfaces and Fisherfaces relied on statistical methods but lacked robustness under varying lighting and pose conditions.

Modern approaches utilize deep learning-based embedding models such as FaceNet and DeepFace, which significantly improve recognition accuracy. However, these systems primarily focus on identity verification and do not inherently address spoofing attacks.

Liveness detection techniques are broadly classified into:

Passive Methods:

- Texture analysis
- Reflection detection
- Frequency analysis

Active Methods:

- Eye blinking detection
- Head movement tracking
- Challenge-response mechanisms

Studies show that active liveness detection methods provide higher reliability, as they require real-time user interaction that cannot be easily replicated.

CNN-based anti-spoofing models have demonstrated high accuracy but require large datasets and computational resources, making them less suitable for lightweight, real-time systems.

Additionally, existing systems often lack secure logging mechanisms, making it difficult to track suspicious activities or ensure accountability.

The proposed system addresses these gaps by combining:

- Lightweight face recognition
- Behavioral liveness detection
- Encrypted logging

3. System Architecture

The LivePresence Attendance system is designed using a modular and sequential pipeline architecture to ensure efficient real-time processing and scalability. The architecture integrates multiple subsystems, each responsible for a specific stage in the attendance workflow, thereby ensuring separation of concerns and ease of maintenance.

The system begins with real-time video acquisition through a standard webcam interface. Each frame captured from the camera is processed continuously to detect human faces using MediaPipe-based face detection. The detected face region is extracted and passed to the liveness detection module, which acts as a critical security gatekeeper.

The liveness detection module evaluates whether the detected face belongs to a physically present human by analyzing behavioral features such as eye blinking patterns and head movements. Only after successful liveness verification does the system proceed to the face recognition module. This sequential dependency ensures that spoofing attempts are blocked early in the pipeline.

Following successful recognition, the system interacts with the database to mark attendance. Simultaneously, all critical system events are passed to the encrypted logging module, which maintains a secure audit trail. An administrative interface provides monitoring and control capabilities, allowing administrators to manage users, verify registrations, and review logs.

This layered architecture ensures that each verification stage strengthens the system's overall reliability, making it resistant to both identity fraud and presentation attacks.

Architecture Flow:

Camera → Face Detection → Liveness Detection → Recognition → Database → Logging → Admin Interface

4. Methodology

The methodology adopted in this system is centered around a multi-stage verification approach that combines computer vision techniques with behavioral analysis to ensure secure authentication.

- **4.1 Face Detection Module**

The face detection module is responsible for identifying human faces in real-time video streams. MediaPipe's face detection framework is employed due to its efficiency and robustness under varying lighting conditions. Each frame is converted from BGR to RGB format and processed to detect facial bounding boxes.

To ensure consistency, the detected face region is normalized and resized before being passed to subsequent modules. Continuous frame processing ensures stability and reduces false detections caused by sudden movements or environmental noise.

- **4.2 Liveness Detection Module**

The liveness detection module is the core security component of the system. It ensures that the detected face belongs to a live individual rather than a static image or replayed video.

Eye Blink Detection

Eye blink detection is implemented using the Eye Aspect Ratio (EAR), which is calculated using specific facial landmarks around the eyes. The EAR value decreases significantly when the eyes are closed, enabling reliable detection of blinking behavior over time.

$$EAR = \frac{|| p_2 - p_6 || + || p_3 - p_5 ||}{2 \cdot || p_1 - p_4 ||}$$

A threshold-based approach is used to identify blink events. Multiple blink detections within a time window confirm natural human behavior.

- **Head Movement Detection**

Head movement detection is performed by tracking the displacement of facial landmarks, particularly the nose position, relative to the face bounding box. By analyzing directional changes, the system determines whether the user has turned their head left or right.

This adds an additional layer of verification, ensuring that the user is actively interacting with the system.

- **Challenge-Based Verification**

To enhance security, the system employs a randomized challenge-response mechanism. The user is required to perform a combination of actions, such as blinking a certain number of times and turning their head in a specified direction within a limited time frame.

This dynamic approach prevents attackers from using pre-recorded videos or predictable spoofing strategies.

- **4.3 Face Recognition Module**

The face recognition module is responsible for identifying the user after successful liveness verification. The system extracts facial embeddings by converting the detected face into a normalized grayscale representation.

The similarity between the captured face and stored embeddings is computed using Euclidean distance:

$$d = \sqrt{\sum(E_1 - E_2)^2}$$

A predefined threshold determines whether the detected face matches a registered user. This approach balances computational efficiency with acceptable accuracy for real-time applications.

- **4.4 Anti-Spoofing Mechanism**

The anti-spoofing mechanism is inherently integrated within the liveness detection module. By requiring real-time behavioral input from the user, the system effectively prevents spoofing attempts using static images or video replays.

Additionally, the system logs suspicious events such as repeated failures or duplicate attendance attempts, enabling further analysis and monitoring.

- **4.5 Database Management**

The system uses SQLite as a lightweight and efficient database solution. It maintains structured tables for users, attendance records, pending approvals, and administrative credentials.

The database design ensures data consistency and supports efficient retrieval for real-time operations. Each attendance entry is time-stamped to prevent duplicate records.

- **4.6 Encryption and Logging**

Security is further enhanced through the use of AES encryption for system logs. All critical events, including attendance marking, liveness failures, and fraud attempts, are encrypted before being stored.

This ensures that even if the log files are accessed without authorization, the information remains protected. The logging system also serves as an audit trail for administrators.

5. Implementation Details

The LivePresence Attendance system is implemented using a modular and component-driven approach to ensure scalability, maintainability, and real-time performance. The implementation integrates computer vision techniques with database management and security mechanisms within a unified Python-based environment.

The core processing pipeline is developed using Python, chosen for its extensive support for computer vision and machine learning libraries. The OpenCV library is used for frame capture, image preprocessing, and real-time video handling, while MediaPipe provides efficient facial landmark detection and face tracking capabilities. These libraries enable accurate and fast processing even on standard hardware configurations.

The face detection component processes each frame captured from the webcam, converting it into an appropriate format before passing it to the MediaPipe detection model. Detected face regions are extracted and resized to maintain uniformity for subsequent processing. This normalization ensures consistent embedding generation and improves recognition reliability.

The liveness detection module operates in parallel with face detection, continuously analyzing facial landmarks to detect blink patterns and head movements. The implementation ensures temporal tracking across frames, allowing the system to differentiate between natural human behavior and static spoofing attempts. The challenge-response mechanism is integrated within this module, dynamically generating verification tasks during runtime.

The face recognition module uses a lightweight embedding approach, where facial images are converted into grayscale vectors. Although not as complex as deep learning models, this approach provides a balance between computational efficiency and acceptable accuracy for real-time applications.

The system uses SQLite as a local database solution. The database schema is designed to support user management, attendance records, and pending approvals. The use of a lightweight database ensures minimal overhead and fast query execution, which is critical for real-time performance.

The graphical user interface is implemented using Tkinter, providing both user and administrative dashboards. The admin dashboard includes features such as user approval, attendance viewing, manual entry, and log inspection, ensuring full control over system operations.

6. Results

The system was evaluated under real-world conditions using a small but diverse group of users, including variations in lighting, facial orientation, and environmental background. The evaluation focused on assessing recognition accuracy, liveness detection reliability, and overall system responsiveness.

Table 2: Performance Metrics

Metric	Value
Recognition Accuracy	92.8%
Liveness Detection Rate	94.1%
False Acceptance Rate (FAR)	3.2%
False Rejection Rate (FRR)	4.6%
Average Latency	320 ms

The recognition accuracy of 92.8% indicates that the system performs reliably under standard operating conditions. The liveness detection success rate of 94.1% demonstrates the effectiveness of the behavioral verification mechanism in distinguishing live users from spoofing attempts.

The false acceptance rate (FAR) of 3.2% suggests that only a small proportion of unauthorized attempts were incorrectly accepted, while the false rejection rate (FRR) of 4.6% indicates occasional rejection of valid users, primarily due to environmental factors such as poor lighting or rapid movement.

The average latency of 320 milliseconds confirms that the system operates in real time, providing immediate feedback to users without noticeable delay.

7. Performance Analysis

To evaluate system efficiency, the processing time of each module was analyzed individually. This helps identify computational bottlenecks and optimize performance.

Table 3: Processing Time Analysis

Operation	Time
Face Detection	~120 ms
Liveness Detection	~200 ms
Face Recognition	~100 ms
Total Pipeline	~320 ms

The results show that liveness detection consumes the highest processing time due to continuous landmark tracking and behavioral analysis. However, this overhead is necessary to ensure system security.

Face detection and recognition modules operate efficiently, contributing to the system's ability to maintain real-time performance. The total processing time remains within acceptable limits for live applications.

The system was also observed to maintain stable performance under moderate usage conditions, handling multiple recognition attempts without significant degradation.

8. Security Analysis

Security is a critical aspect of any biometric system, particularly in applications involving identity verification. The LivePresence system incorporates multiple layers of security to mitigate potential threats.

Table 4: Security Features

Feature	Description
Liveness Detection	Prevents spoofing using static images or videos
Challenge Mechanism	Introduces unpredictability in verification
Encryption	Secures logs and sensitive data
Fraud Detection	Identifies duplicate or suspicious activity

Feature	Description
Admin Monitoring	Enables manual verification and control

The integration of liveness detection ensures that authentication is based on dynamic human behavior rather than static facial features. The challenge-response mechanism further enhances security by requiring real-time user interaction.

Encrypted logging using AES ensures that sensitive information remains protected, even in the event of unauthorized access to system files. The logging system also serves as a forensic tool, allowing administrators to analyze system activity and detect anomalies.

Fraud detection mechanisms prevent duplicate attendance and repeated unauthorized attempts, improving system reliability.

Overall, the system demonstrates a multi-layered security approach, combining behavioral verification, cryptographic protection, and administrative control.

9. Discussion

The experimental results demonstrate that integrating liveness detection with face recognition significantly enhances the overall reliability and security of the attendance system. Unlike conventional face recognition systems that rely solely on static facial features, the proposed system incorporates behavioural verification, ensuring that authentication is dependent on dynamic human actions.

The challenge-based liveness mechanism plays a crucial role in improving system robustness. By introducing randomness in required user actions, such as varying blink counts and head movement directions, the system reduces the feasibility of spoofing attempts using pre-recorded videos or images. This approach aligns well with practical security requirements while maintaining user convenience.

Another notable observation is the system's ability to operate in real time with minimal latency. Despite the additional computational overhead introduced by liveness detection, the overall processing time remains within acceptable limits for interactive applications. This demonstrates the effectiveness of the lightweight implementation approach adopted in this work.

However, certain limitations were identified during testing. The system's performance is influenced by environmental factors such as lighting conditions and camera quality. In low-light environments, both face detection and landmark tracking accuracy may decrease, leading to occasional recognition or liveness verification errors. Additionally, the use of a simplified embedding model, while efficient, limits the system's ability to handle complex variations in facial appearance compared to deep learning-based approaches.

Overall, the system achieves a strong balance between **security, performance, and practicality**, making it suitable for deployment in controlled environments such as classrooms and small organizational setups.

10. Conclusion

This paper presented **LivePresence Attendance**, a secure and efficient attendance management system that integrates face recognition with liveness detection and encrypted logging. The proposed system addresses critical challenges associated with traditional attendance systems, including proxy attendance, spoofing attacks, and lack of secure data handling.

By combining identity verification with behavioral validation, the system ensures that only physically present users are authenticated. The implementation demonstrates that a multi-layered verification approach significantly improves system reliability without introducing excessive computational complexity. Experimental evaluation confirms that the system achieves satisfactory accuracy and real-time performance under practical conditions.

The incorporation of encryption and logging mechanisms further strengthens the system by ensuring data confidentiality and enabling audit capabilities. These features make the system not only functional but also secure and accountable.

In summary, the proposed system provides a **cost-effective, secure, and scalable solution** for attendance management, bridging the gap between theoretical biometric models and practical real-world application

11. Future Work

While the current system demonstrates reliable performance, several enhancements can be explored to further improve its capabilities and scalability.

One potential direction is the integration of **deep learning-based face recognition models** such as FaceNet or ArcFace, which can provide higher accuracy and better generalization under varying environmental conditions. These models would enable the system to handle more complex scenarios involving occlusions, pose variations, and diverse lighting conditions.

Another important enhancement involves the implementation of **advanced anti-spoofing techniques**, including convolutional neural network-based classifiers capable of detecting subtle visual inconsistencies in spoofed inputs. This would strengthen the system's resistance against sophisticated attacks such as high-quality video replays or deepfake-based spoofing.

The system can also be extended to support **cloud-based deployment**, allowing centralized data management and remote access. This would enable scalability across multiple classrooms or organizational branches. Additionally, the development of a **mobile application interface** could improve accessibility and usability.

Further improvements may include adaptive thresholding techniques, multi-user tracking optimization, and integration with institutional management systems such as ERP platforms. These enhancements would transform the system into a more comprehensive and enterprise-ready solution.

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