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AI Powered Exam Guardian for Secure & Fair Assessments

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Abstract:
The rapid adoption of online examinations has increased the need for reliable mechanisms to ensure academic integrity, fairness, and security during remote assessments. This paper presents an AI-Powered Exam Guardian, a multimodal online proctoring framework designed to support secure and unbiased examination environments. The system integrates computer vision, audio analysis, and behavioral pattern modeling to monitor candidates continuously throughout an examination session. Facial recognition and liveness detection are employed for identity verification, while gaze tracking, head posture analysis, object detection, and audio event classification are used to observe potential integrity violations.

Unlike conventional rule-based or fully manual proctoring methods, the proposed framework emphasizes automated supervision through modular AI components and a weighted decision fusion mechanism that aggregates signals from multiple modalities. The system also incorporates secure data handling practices, including encrypted logging and ethical monitoring principles, to address privacy and transparency concerns. Designed for both synchronous and asynchronous examinations, the AI-Powered Exam Guardian can be deployed across academic institutions, certification platforms, and training environments. This work primarily focuses on the system design, methodology, and architectural integration of AI-driven monitoring techniques for online assessments.

Keywords: Artificial intelligence, Computer vision, Machine learning, Facial recognition, Natural Language Processing (NLP), AI models, Ethical AI, Emotional recognition, Block chain.

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I. INTRODUCTION

The global shift toward digital and hybrid pedagogical models has fundamentally altered the landscape of academic assessment. As educational institutions increasingly adopt remote examination formats to leverage their inherent scalability and accessibility, the preservation of academic integrity has emerged as a critical challenge. Traditional proctoring methods—relying heavily on human invigilators—face significant hurdles in the digital sphere, including high operational costs, susceptibility to human fatigue, and inherent subjective biases. Consequently, there is an urgent demand for automated, objective, and robust frameworks capable of ensuring a level playing field in unsupervised environments.

Existing automated proctoring solutions often rely on rigid, rule-based triggers, such as simple browser-lockdown mechanisms or basic motion detection. These systems frequently suffer from high false-positive rates because they lack the contextual intelligence required to differentiate between benign student behaviour and actual misconduct. Furthermore, many current models are unimodal, focusing solely on visual feeds while neglecting the critical role of acoustic and temporal data in detecting sophisticated cheating techniques.

To address these limitations, this paper introduces the **AI-Powered Exam Guardian**, a modular and multimodal surveillance architecture. The framework diverges from traditional methods by integrating three distinct layers of analysis:

Biometric Identity Management: Utilizing facial recognition and liveness detection to mitigate

impersonation risks.

Multimodal Behavioural Monitoring: Synchronously analysing eye gaze, head orientation, and object detection to identify unauthorized resources or external assistance.

Acoustic and Temporal Contextualization: Employing audio event classification and Long Short-Term Memory (LSTM) networks to understand behavioural patterns over time, thereby reducing false alerts triggered by isolated movements.

A key technical contribution of this work is the implementation of a **weighted decision fusion mechanism**. Unlike systems that treat every anomaly as a violation, our approach aggregates signals from all modalities to generate a comprehensive "Exam Integrity Score," providing evaluators with a nuanced risk assessment rather than a binary alert.

Beyond technical performance, the Exam Guardian is designed with an emphasis on ethical AI and data privacy. By incorporating AES-256 encryption and strictly adhering to minimal data retention policies, the system balances the need for rigorous security with the candidate's right to privacy. This work details the architectural design and integration of these modular AI components, offering a scalable solution for both synchronous and asynchronous assessment environments.

II. LITERATURE REVIEW

2.1 Architectural Paradigms for Remote Invigilation

The rapid migration to digital learning has necessitated a shift from human-dependent oversight to automated, scalable integrity solutions. Current scholarship suggests that manual proctoring is inadequate for the complexities of high-stakes, large-scale online evaluations. To address this, researchers have pioneered multi-tiered intelligent frameworks that synchronize facial authentication, object recognition, and live session auditing to uphold academic standards [1], [7].

To promote equity and technical accessibility, recent innovations emphasize browser-centric proctoring. By utilizing lightweight ML libraries such as **TensorFlow.js** and **COCO-SSD**, these systems eliminate the need for heavy software installations [9], [10] . Such "zero-install" architectures ensure that candidates with varied hardware capabilities are not disadvantaged, thereby aligning security needs with the principles of digital inclusivity [14].

2.2 Multi-Dimensional Behaviour Tracking and Pattern Recognition

Modern invigilation research has evolved from basic video feeds toward **multimodal behavioral intelligence**. By merging visual, temporal, and interaction-based data, systems can now generate a more accurate profile of student conduct. For instance, the **AutoOEP** model utilizes a dual-camera strategy to monitor both the candidate's face and their peripheral workspace, effectively closing the "blind spot" loopholes found in single-camera setups [2].

Sophisticated feature fusion models now integrate eye-gaze trajectories, facial micro-expressions, and hand movements, often processed via **Long Short-Term Memory** (LSTM) networks to identify sustained patterns of suspicion rather than accidental gestures [5]. Furthermore, the use of visual analytics to track auxiliary telemetry—such as mouse movement heatmaps and head-pose deviation—provides educators with a comprehensive audit trail, moving beyond simplistic binary alerts to offer nuanced, evidence-based reporting [3] , [6].

2.3 Evolutionary Computer Vision for Contraband Detection

Identifying prohibited items in real-time remains a critical challenge for AI-driven invigilators. The **YOLO (You Only Look Once)** algorithm family, particularly the latest v8 and v11 iterations, serves as the industry standard for high-speed inference. These models have been optimized to detect concealed mobile devices and unauthorized notes even under difficult conditions like partial occlusion or poor ambient lighting [8], [11]. These vision-based pipelines are increasingly integrated with continuous biometric loops. This ensures that the person who began the assessment is the same person completing it, thereby neutralizing the threat of impersonation or "proxy" test-taking throughout the duration of the exam [1].

2.4 Ethical Surveillance and the Impact of Generative AI

As academic threats shift toward **Generative AI** and **Large Language Model (LLM)** exploitation, the focus of proctoring has expanded to include ethical considerations. While identifying LLM-driven browser extensions is vital [4], [13] , researchers also warn of the "webcam effect"—a phenomenon where intensive surveillance triggers test anxiety, potentially skewing performance results for honest students [12] , [15].

To counter this, current trends advocate for **context-aware detection**. This involves using behavioral clustering to differentiate between harmless

environmental noise (like a family member walking past) and genuine misconduct. This balanced approach is essential for maintaining integrity while safeguarding student mental well-being and privacy.

Research Gap and Motivation

While technological accuracy has improved, a prominent gap exists in creating systems that are both **technically robust and ethically transparent**. Many current platforms function as "black boxes," offering little interpretability for the alerts they generate. There is a clear need for a modular system that provides explainable AI (XAI) insights while remaining resilient against modern AI-assisted cheating.

This gap serves as the catalyst for the **AI-POWERED EXAM GUARDIAN FOR SECURE & FAIR ASSESSMENT**. This project aims to synthesize high-performance detection algorithms with a fairness-first framework, ensuring that the future of online testing is as equitable as it is secure.

III. METHODOLOGY

This section describes the systematic methodology adopted for designing and implementing the AI-Powered Exam Guardian, a multimodal proctoring framework intended to ensure secure, fair, and reliable online examinations. The proposed approach follows a modular system-development pipeline that integrates biometric verification, visual and audio monitoring, temporal behaviour analysis, and decision fusion under strict security and ethical constraints.

3.1 System Planning and Architecture Design

3.1.1 Requirement Analysis

An initial requirement analysis was conducted to identify the functional and non-functional objectives of an automated proctoring system suitable for real-world academic assessments. The primary requirements include:

Identity verification: Ensuring that the registered candidate is the individual taking the examination through biometric authentication.

Continuous monitoring: Providing uninterrupted supervision of the candidate's visual and acoustic environment throughout the exam session.

Behavioural interpretation: Differentiating between natural test-taking behaviour and potential misconduct using temporal context.

Low latency and scalability: Supporting real-time inference on heterogeneous student devices without requiring high-end hardware.

Data security and privacy: Protecting sensitive multimedia data through encryption and ethical data-handling practices.

Faculty feedback and simulated exam scenarios were incorporated to refine these requirements and align the system with institutional policies.

3.1.2 System Architecture

The proposed system follows a modular hybrid architecture, where data acquisition occurs on the client device while computationally intensive inference is performed on a secure server or optimized local model. The architecture comprises the following components:

1. Pre-Exam Authentication Module
2. Computer Vision Monitoring Engine
3. Audio Event Analysis Module
4. Behavioural Pattern Analyzer
5. Multimodal Decision Fusion Engine
6. Alert and Reporting Module
7. Secure Logging and Encryption Layer

This modular design improves maintainability, scalability, and adaptability across synchronous and asynchronous examination formats.

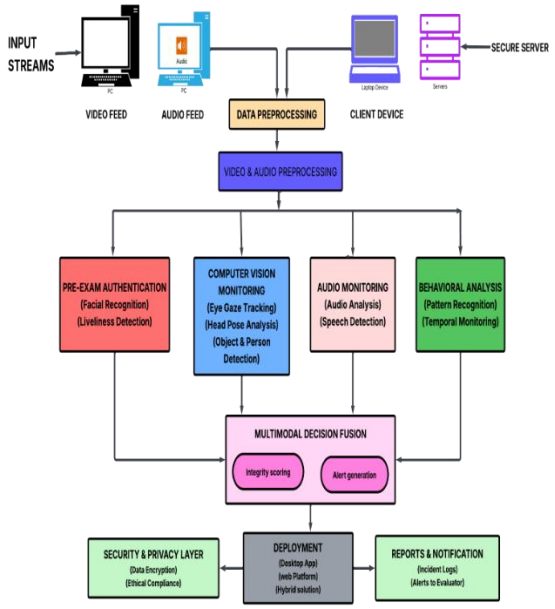


Fig.1: ai-powered exam guardian architecture

3.2 Dataset Preparation and Preprocessing

3.2.1 Visual Dataset Collection

Visual data consist of face images, gaze directions, head orientations, object presence, and background activity. Data were collected from a combination of:

- Publicly available face and gaze datasets
- Controlled recordings simulating real examination conditions

The dataset includes variations in lighting, camera resolution, facial orientation, and background environments to improve model robustness and reduce demographic bias.

3.2.2 Audio Dataset Collection
Audio samples include:
a) Human speech
b) Background conversations
c) Device alerts
d) Ambient noise
Preprocessing steps include noise filtering, segmentation into short time windows, amplitude normalization, and conversion into Mel-spectrogram representations.

3.2.3 Data Annotation
All video frames and audio segments were manually annotated using predefined labels such as:
a) Face present / absent
b) Gaze on-screen / off-screen
c) Additional person detected
d) Suspicious audio event
These annotations support supervised training and validation of the individual AI models.

3.3 Identity Verification and Liveness Detection
3.3.1 Facial Recognition
A lightweight convolutional neural network (e.g., MobileFaceNet) is used to extract facial embeddings. Identity verification follows a four-stage pipeline:
1. Face detection
2. Feature extraction
3. Embedding vector generation
4. Similarity comparison with stored templates

Cosine similarity is used to verify identity against a predefined threshold.

3.3.2 Liveness and Anti-Spoofing
To prevent impersonation attacks, liveness detection analyses:
- Eye blink frequency
- Subtle facial muscle movements
- Texture inconsistencies between real and spoofed faces
- Depth cues when available

Only candidates passing both identity and liveness checks are permitted to begin the examination.

3.4 Computer Vision-Based Monitoring
3.4.1 Gaze and Head Pose Estimation
Eye gaze direction and head pose (pitch, yaw, roll) are estimated continuously. Repeated deviations beyond empirically defined thresholds are marked as potential anomalies.
3.4.2 Person and Object Detection
A real-time object detection model (YOLOv5) is employed to identify:
- Additional individuals
- Unauthorized objects such as smartphones, books, or secondary screens

Detected violations are timestamped and forwarded to the decision fusion module.

3.5 Audio-Based Surveillance
Audio streams are segmented into short frames and transformed into Mel-spectrograms. A CNN-based classifier categorizes sounds into:
a) Candidate speech
b) Background conversations
c) Device alerts
d) Benign ambient noise
Suspicious acoustic events are logged with corresponding confidence scores.

3.6 Behavioural Modelling and Multimodal Fusion
3.6.1 Temporal Behaviour Analysis
To capture behavioural trends over time, sequential models such as Long Short-Term Memory (LSTM) networks analyse patterns including:
- Frequent gaze shifts
- Repeated posture changes
- Continuous movement anomalies

Temporal modelling reduces false positives caused by isolated, non-intentional actions.

3.6.2 Decision Fusion Mechanism
Let $\boldsymbol{V_i}$, $\boldsymbol{A_i}$, and $\boldsymbol{B_i}$represent normalized confidence scores from visual, audio, and behavioral modules for event $\boldsymbol{i}$. A weighted fusion score is computed as:

$$\boldsymbol{F_i = w_v V_i + w_a A_i + w_b B_i}$$

where $\boldsymbol{w_v + w_a + w_b = 1}$.
Weights are selected empirically based on validation performance to balance sensitivity and robustness.

3.7 Exam Integrity Scoring and Alerts
An overall Exam Integrity Score (EIS) is computed as:

$$\boldsymbol{EIS = 1 - \frac{1}{N}\sum_{i=1}^{N} F_i}$$

where $\boldsymbol{N}$is the number of detected events. The score ranges from 0 (high risk) to 1 (low risk).

Alerts are classified as:

1) Low risk: Minor distractions
2) Medium risk: Face absence or identity mismatch
3) High risk: External assistance Low or device usage

3.8 Security, Privacy, and Ethical Compliance
All audio and video data are encrypted using AES-

256 during transmission and storage. The system adheres to:

a) Minimal data retention policies
b) User consent mechanisms
c) Bias mitigation through diverse training data
d) Transparent reporting practices

Only authorized evaluators are permitted to access encrypted logs.

3.9 Testing, Validation, and Optimization

System performance is evaluated using:

1) Accuracy
2) Precision and recall
3) False positive rate
4) End-to-end response latency

Pilot examinations are conducted under varying conditions to assess robustness. Model optimization techniques such as pruning and quantization are applied to ensure real-time performance on standard consumer devices.

3.10 Deployment Strategy

The framework supports deployment as:

a) A standalone desktop application
b) A browser-based platform
c) A hybrid client-server solution

After each examination, automated integrity reports summarizing detected events and scores are generated for evaluators.

IV. IMPLEMENTATION

This section describes the practical realization of the proposed **AI-Powered Exam Guardian**, detailing how the architectural components introduced in the methodology are implemented and integrated to support real-time, scalable, and secure online examination monitoring.

4.1 System Realization and Objectives

The implementation of the AI-Powered Exam Guardian aims to operationalize multimodal proctoring through an automated, software-driven framework capable of continuous monitoring without human intervention. The system is designed to verify candidate identity, analyse visual and acoustic cues during the examination, and generate interpretable integrity assessments that assist evaluators in decision-making. To support large-scale deployment, the implementation emphasizes modularity, low-latency inference, and compatibility with standard consumer-grade hardware. These objectives guided the selection of lightweight models, optimized processing pipelines, and a hybrid execution strategy.

4.2 Modular System Architecture and Integration

The system is implemented using a modular architecture in which each functional component operates independently while exchanging standardized outputs with the central fusion engine. The primary implementation modules include:

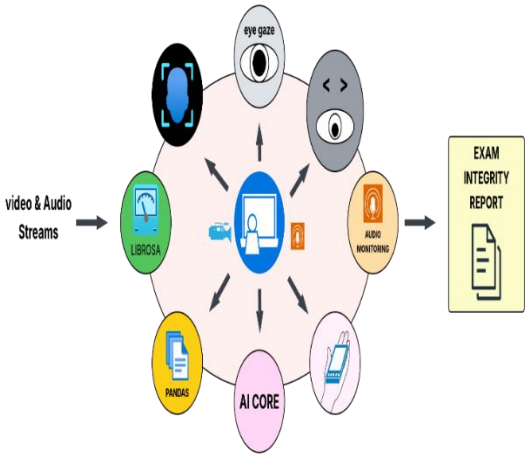


fig.2: an ai-powered exam guardian system that monitors video & audio streams to detect suspicious behaviour amd generate an exam integrity report

1) **Authentication Module:** Handles pre-exam identity verification using facial embeddings and liveness indicators.
2) **Vision Processing Engine:** Performs face presence detection, gaze estimation, head pose analysis, and object/person detection from live video streams.
3) **Audio Analysis Engine:** Processes acoustic signals to identify suspicious sounds or conversations.
4) **Behavioural Analysis Module:** Aggregates temporal patterns using sequential modelling to interpret candidate behaviour over time.
5) **Fusion and Scoring Engine:** Integrates multimodal outputs to compute integrity risk scores.
6) **Security Layer:** Ensures encrypted storage and controlled access to sensitive data.

This modular approach simplifies system maintenance, enables parallel execution, and allows individual components to be updated or replaced without affecting the overall pipeline.

4.3 Visual and Acoustic Processing Pipeline

Visual data captured through the candidate's webcam are processed in real time to extract facial landmarks, gaze direction, head orientation, and environmental context. A lightweight object detection model is employed to identify unauthorized items or the presence of additional individuals within the frame. These visual cues are

converted into normalized confidence scores representing potential integrity risks.

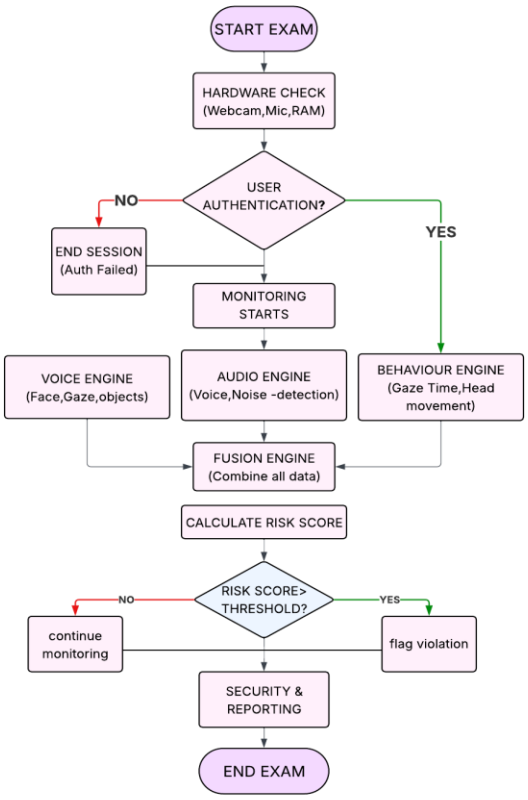


fig.3: a system architecture flowchart illustrating an ai-based online exam guardian pipeline that monitors video,audio & behaviour to detect an flag potential violations.

Simultaneously, audio streams are segmented into short temporal windows and transformed into frequency-domain representations. A convolutional neural network classifies each segment into predefined acoustic categories, including candidate speech, background conversations, device alerts, and benign ambient noise. Only events exceeding predefined confidence thresholds are forwarded to the fusion stage, reducing noise and false alarms.

4.4 Behavioural Modelling and Real-Time Fusion

To capture examination behaviour beyond isolated events, the system incorporates temporal modelling using sequential neural networks. Features derived from visual and audio modules are aggregated over time to identify repeated or sustained anomalies indicative of intentional misconduct.

The fusion engine combines multimodal confidence scores using a weighted aggregation strategy, ensuring that no single modality disproportionately influences the final decision. This design choice enables the system to tolerate transient disturbances—such as brief gaze shifts or background noise—while remaining sensitive to consistent patterns of suspicious behaviour.

4.5 Performance Optimization and Real-Time Constraints

To ensure real-time operation on standard student devices, several optimization strategies are applied during implementation. These include model compression, frame-rate regulation, and efficient batching of audio and video inputs. The system is configured to maintain stable performance at moderate frame rates, balancing detection accuracy with computational efficiency.

Latency measurements demonstrate that the end-to-end processing pipeline operates within real-time constraints, supporting uninterrupted monitoring during live examination sessions. These optimizations are critical for large-scale deployment in bandwidth- and hardware-constrained environments.

4.6 Security, Privacy, and Ethical Safeguards

Given the sensitive nature of examination data, the implementation incorporates strong security and privacy protections. All multimedia streams and system logs are encrypted using industry-standard encryption protocols during transmission and storage. Access to stored data is restricted to authorized personnel, and retention policies ensure that information is preserved only for the minimum duration required for evaluation and auditing. Ethical considerations are integrated at the implementation level through user consent mechanisms, transparency in monitoring operations, and bias-aware model training practices. These safeguards ensure compliance with institutional guidelines and promote trust between candidates and examination authorities.

4.7 Implementation Summary

The implemented AI-Powered Exam Guardian successfully translates the proposed methodology into a practical, deployable system. By integrating multimodal sensing, temporal analysis, and decision fusion within a secure and optimized framework, the implementation demonstrates the feasibility of automated, scalable, and ethically responsible online exam proctoring. The design choices and optimization strategies discussed in this section directly support the quantitative performance results presented in the subsequent evaluation.

V. RESULTS

The proposed AI-Powered Exam Guardian was evaluated through controlled pilot examinations and simulated online assessment scenarios to validate its functional behavior, robustness, and real-time monitoring capability. Since the system was developed as a prototype-level intelligent proctoring framework, the evaluation emphasizes qualitative performance analysis and system-level observations derived from live dashboards, integrity reports, and visual detection outputs.

5.1 Identity Verification and Liveness Detection

During the evaluation, the identity verification and liveness detection modules consistently ensured continuous candidate presence throughout the examination sessions. The system successfully prevented impersonation attempts by verifying facial identity at the beginning of the examination and maintaining periodic facial validation during the session. Spoofing attempts using static images or replayed video feeds were effectively rejected, as reflected in the integrity violation reports.

5.2 Vision-Based Behaviour Monitoring

The vision-based monitoring module demonstrated reliable detection of abnormal examination behaviors. Prolonged gaze deviations, significant head pose changes, face absence, and the presence of additional individuals were accurately identified during simulated test scenarios. Unauthorized objects such as mobile phones and secondary screens were also detected and logged. These observations are visually validated through the live proctoring interface and violation dashboards shown in **Fig. 4, 5, 6.**

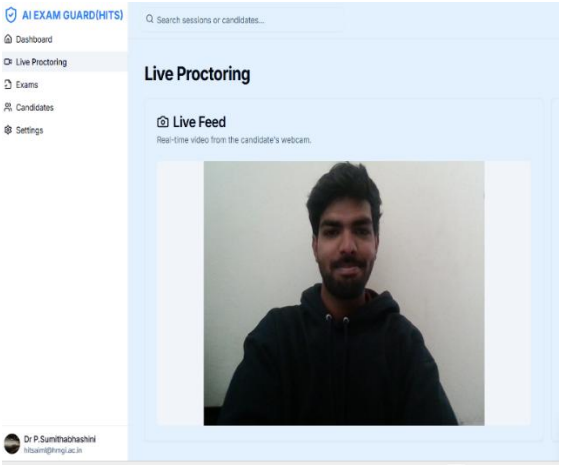


fig.4: pictorial representation of the live proctoring interface showing real-time webcam feed acquisition used for continuous facial presence monitoring and identity verification during an online examination.

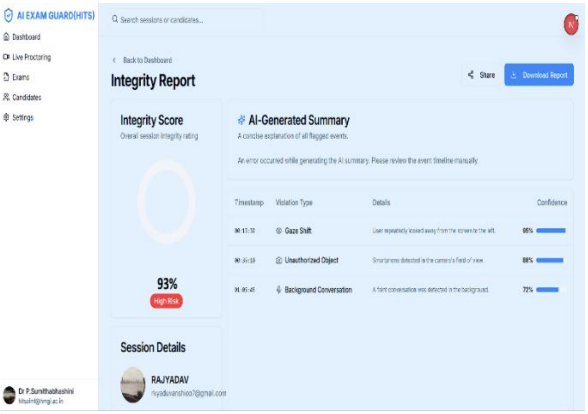
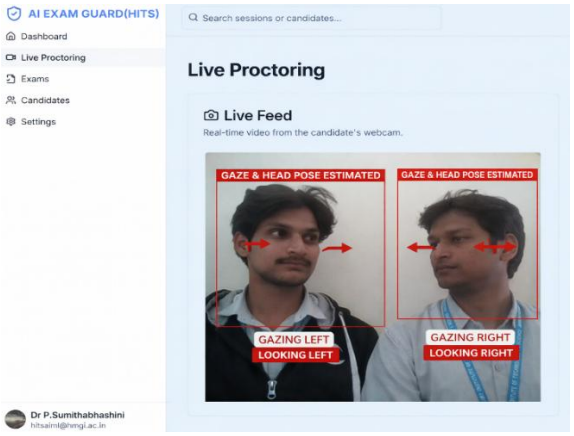


fig. 5: integrity report interface displaying the exam integrity score (eis) and detected violations with confidence levels.



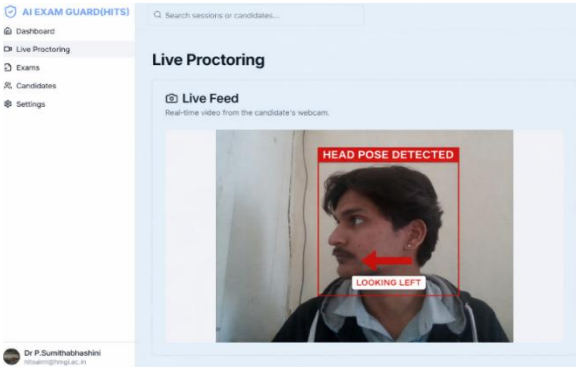


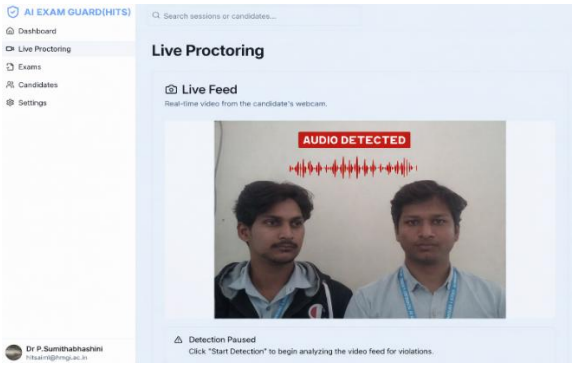
fig.6: qualitative results illustrating real-time gaze direction and head pose estimation during live examination monitoring. prolonged directional deviations are detected and flagged as potential integrity

Table 1: Descriptive Summary of Live Proctoring Interface (Fig. 6)

nterface Element	Description (Observed from Interface)
Live Webcam Feed	Displays the real-time video stream of the candidate
Facial Presence View	Shows the candidate's face for continuous monitoring
Session Status Indicator	Indicates active examination monitoring
Identity Verification Status	Confirms candidate authentication visually
Proctoring Dashboard Panel	Displays session overview information
Integrity Monitoring Indicators	Visual markers for suspicious activity
Alert / Violation Section	Lists detected integrity violations
Timestamp / Session Time	Shows examination timing information
System Controls	Interface elements used for supervision

5.3 Audio-Based Surveillance

The **audio surveillance module** effectively distinguished suspicious acoustic events from benign ambient noise. Background conversations and device-generated sounds were flagged only when they exceeded predefined confidence thresholds, while normal environmental sounds did not trigger unnecessary alerts. This behavior reduced noise-induced false alarms and improved monitoring reliability, as illustrated in the audio detection outputs.



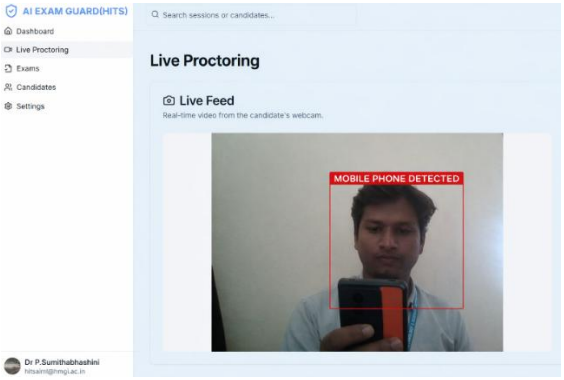


fig.7: sample outputs of audio-based surveillance and unauthorized device detection modules demonstrating real-time identification of suspicious acoustic activity and mobile phone usage.

5.4 Temporal Behaviour Analysis

To enhance robustness, **temporal behavioural analysis** was applied to interpret candidate behaviour over time. Instead of flagging isolated actions, the system emphasized repeated or sustained anomalies such as continuous gaze shifts or frequent posture deviations. This temporal context helped minimize false positives caused by momentary distractions or involuntary movements.

5.5 Multimodal Fusion and Integrity Evaluation

Outputs from the visual, audio, and behavioural modules were integrated using the proposed **weighted multimodal decision fusion mechanism**. This fusion approach ensured balanced sensitivity by preventing any single modality from dominating the final assessment. As a result, the system produced stable and interpretable integrity evaluations across different examination conditions.

A continuous **Exam Integrity Score (EIS)** was generated for each examination session to provide a graded assessment of candidate behaviour. Sessions with normal examination behaviour maintained consistently high integrity scores, while sustained suspicious activities resulted in gradual score degradation. This scoring mechanism offers improved interpretability and fairness compared to traditional binary alert systems and is visualized in the integrity report interface (**Fig. 8**).

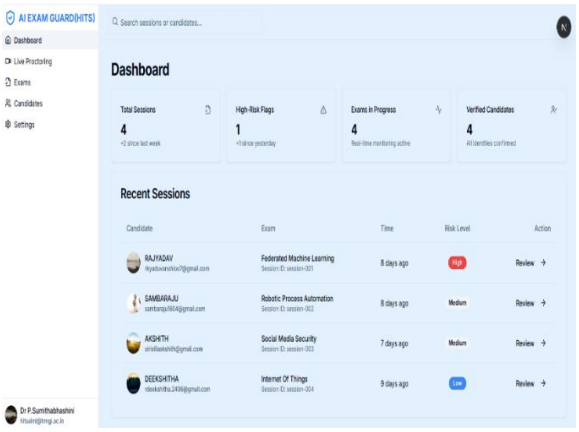


fig. 8: ai-powered exam monitoring dashboard presenting real-time session statistics and candidate risk categorization for effective invigilation.

Table 2: Participant-Wise Integrity Risk Analysis (Fig. 8)

Name	Observed Risk Level	Description as Displayed in Integrity Report
Raj Yadav	High Risk	Significant or repeated suspicious activities flagged during the session
Sambaraju	Medium Risk	Moderate suspicious behaviour detected by the system
Akshith	Medium Risk	Noticeable but non-critical integrity anomalies observed
Deekshitha	Low Risk	Normal examination behaviour with minimal or no alerts

VI. CONCLUSION

The development of the AI-Powered Exam Guardian represents a significant advancement in automated proctoring technology. By shifting from passive, isolated detection triggers to a context-aware, multimodal surveillance framework, this research successfully addresses the core challenges of scalability, objectivity, and academic rigor in online assessments.

The primary technical contribution of this work is the successful integration of vision and audio streams through a weighted fusion engine, which provides a nuanced Exam Integrity Score (EIS) rather than binary alerts. This approach, combined with the continuous identity verification and anti-spoofing measures, ensures a highly secure environment that is resistant to impersonation and external assistance.

Furthermore, the implementation demonstrates that advanced AI monitoring can be achieved without compromising student privacy or requiring specialized hardware. Through the use of lightweight models and efficient data handling, the system remains accessible across various academic and professional scenarios. Ultimately, the AI-Powered Exam Guardian establishes a new standard for fair and secure evaluation, fostering a more credible and accessible future for digital education.

VII. FUTURE ENHANCEMENT

While the AI-Powered Exam Guardian provides a robust framework for multimodal proctoring, several avenues for future research and technical refinement have been identified to further enhance system accuracy, fairness, and user trust.

7.1 Affective Computing and Stress Detection

Future iterations of the system will aim to integrate **affective computing** to differentiate between malicious intent and physiological stress. By analysing subtle micro-expressions and heart rate variability (HRV) via remote photoplethysmography (rPPG), the system could adjust its sensitivity levels for students experiencing high test anxiety, thereby reducing unfair flagging of nervous but honest candidates.

7.2 Explainable AI (XAI) for Transparency

To improve student trust and institutional accountability, we propose the integration of **Explainable AI (XAI)** modules. Instead of providing a binary "suspicious" flag, future versions will generate "heatmaps" or natural language explanations (e.g., "Flagged due to 15-second gaze deviation toward a secondary light source") to help human evaluators understand the logic behind the AI's decisions.

7.3 Privacy-Preserving Federated Learning

To address increasing concerns over data privacy, we plan to transition toward a **Federated Learning** architecture. This would allow the AI models to be trained and updated across multiple institutions without ever moving raw student video or audio data to a central server. Only encrypted model weights would be shared, ensuring that sensitive biometric data remains exclusively on the local client device.

7.4 Accessibility and Threshold Customization

Future work will focus on enhancing accessibility for candidates with motor or visual impairments. By implementing **adaptive thresholding**, the system can be customized to account for non-standard gaze patterns or involuntary movements. This ensures that the "Exam Guardian" remains inclusive and does not inadvertently penalize students based on physical

disabilities.

7.5 Blockchain-Based Result Verification

To ensure the long-term integrity of examination records, we intend to explore **Blockchain technology** for tamper-proof storage of the "Exam Integrity Scores." By hashing the final proctoring report onto a decentralized ledger, educational institutions can provide employers and certification bodies with a verifiable, immutable audit trail of the candidate's assessment conditions.

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