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AI Powered Malpractice Detection System for Exam

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Abstract: This project introduces an automated Examination Malpractice Detection System that utilizes YOLOv8 for real-time object detection and MediaPipe for human pose estimation. By processing live video streams through a Flask-based backend, the system identifies prohibited items and suspicious behavioral patterns such as excessive head movement or unauthorized communication. To ensure high reliability, it employs a 60% confidence threshold and a decision-fusion layer that reduces false positives by analyzing sequences of motion. The architecture features a seamless administrative response layer that captures time-stamped evidence and compiles infractions into a secure zip archive. Upon session completion, the system automatically transmits a comprehensive summary and evidence file to examiners via an integrated email notification service, ensuring a transparent and objective disciplinary review process.
Keywords: Artificial Intelligence, Computer Vision, YOLOv8, Automated Proctoring, Real-Time Detection, Academic Integrity.

I. INTRODUCTION

The integrity of examination systems is a fundamental pillar of the educational process, ensuring that academic success is a true reflection of a student’s knowledge and effort. However, with the increasing complexity of educational environments and the shift toward digital and remote assessments, traditional methods of invigilation are facing unprecedented challenges. Manual proctoring, while historically standard, is often limited by human fatigue, subjective judgment, and an inability to monitor large groups of students with consistent precision. This vulnerability has led to a rise in sophisticated forms of malpractice, necessitating a transition toward more objective, technology-driven solutions.

Recent advancements in computer vision and artificial intelligence have opened new avenues for automating the surveillance of examination halls. By utilizing deep learning architectures, it is now possible to develop systems that can "see" and "interpret" human behavior in real-time. These intelligent frameworks are designed to identify suspicious patterns—such as unauthorized communication or the use of prohibited electronic devices—that might be missed by the human eye. The integration of these technologies aims to create a transparent and fair testing environment where every candidate is held to the same high standard of conduct.

The core of a modern malpractice detection system lies in its ability to perform high-speed object detection and behavioral analysis simultaneously. Utilizing state-of-the-art models like YOLO (You Only Look Once), the system can identify prohibited items such as mobile phones, smartwatches, or unauthorized printed materials with high confidence levels. Simultaneously, human pose estimation techniques allow the system to map skeletal structures and track physical gestures, such as excessive head turning or reaching into pockets. This dual-layered approach ensures a comprehensive monitoring coverage that spans both physical contraband and deceptive body language.

One of the significant technical hurdles in automated proctoring is the reduction of false positives, where natural movements are incorrectly flagged as cheating. To address this, the current project implements advanced machine learning classifiers that act as a decision-making layer, weighing various inputs before confirming a violation. By analyzing a sequence of events rather than isolated frames, the system can distinguish between a student stretching their neck and a student intentionally looking at a neighbor’s script. This refinement is crucial for maintaining a balance between strict enforcement and a non-intrusive testing experience. In addition to visual monitoring, a robust detection system must ensure accountability through seamless identity verification. By integrating real-time facial recognition and bio-data matching, any detected infraction can be immediately and accurately linked to a specific student’s institutional record.

This creates an immutable digital trail of evidence, including time-stamped video snippets and student information, which provides administrative bodies with the necessary tools for objective disciplinary review. Such a system removes the "human element" of potential bias or oversight, ensuring that the consequences of malpractice are applied fairly and based on empirical data.

Ultimately, the goal of this major project is to develop a scalable, low-latency, and highly accurate Examination Malpractice Detection System. By leveraging full-stack development frameworks and high-performance deep learning models, the project provides a comprehensive solution for both physical classrooms and remote proctoring environments. As educational institutions worldwide continue to adapt to a digital-first reality, the deployment of such intelligent systems is not merely a technical upgrade, but a vital step in preserving the long-term value and credibility of academic certifications.

II. LITERATURE SURVEY

The rapid evolution of educational technology and the shift toward digital assessment platforms have necessitated more sophisticated methods for maintaining academic integrity. As traditional invigilation faces challenges related to scalability and human error, researchers have increasingly turned to Artificial Intelligence (AI) and Machine Learning (ML) to develop automated proctoring solutions. This literature survey examines a diverse range of recent studies, including systematic reviews of deep learning architectures, practical implementations of pose estimation and biometric tracking, and institutional assessments of ICT adoption. By analyzing these various approaches—ranging from real-time video surveillance using Convolutional Neural Networks to behavioral analysis via XGBoost—this section provides a comprehensive overview of the current state of automated malpractice detection and identifies the technological gaps that the present research aims to address.

Shruthi and Chethan (2025) conducted a systematic review of machine learning techniques used in intelligent proctoring systems, specifically focusing on the shift toward deep learning. The authors analyzed various system components such as face detection, face spoofing, and head pose estimation, noting the evolution of models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) in addressing real-time cheating detection. Their survey highlights that while deep learning has significantly improved accuracy, the field still faces challenges regarding diverse datasets and the ethical implications of automated surveillance.

Ahmed and Mohammed (2025) presented a comprehensive review of automated cheating detection systems for both online and in-person examinations. Their research evaluated multiple technological approaches, including behavioral analysis, facial expression tracking, and voice analysis. They found that integrating CNN, RNN, and YOLO models has greatly enhanced the scalability and accuracy of identifying suspicious behaviors, though they emphasize the need for these systems to adapt to varied testing conditions and larger exam settings.

Ofor-Douglas (2026) examined the implementation of artificial intelligence to minimize examination malpractice within the Nigerian university system. The study argues that traditional human-led invigilation is often compromised by "human elements" such as bribery and corruption. By contrast, the author suggests that AI-driven technology provides a more objective and just assessment environment, urging university administrators to adopt these tools to root out long-standing malpractice habits.

Kalagbor-Gbeke (2026) utilized a descriptive survey design to investigate the integration of AI tools for managing exam malpractice in public tertiary institutions in Rivers State, Nigeria. The study involved a stratified random sample of 429 lecturers across eight institutions to assess current implementation levels and readiness. The findings, validated by a reliability index of 0.83, provide a baseline for how educational management can utilize AI to enhance academic integrity at the institutional level.

Ayonote (2025) assessed the usage of Information and Communication Technology (ICT) in controlling malpractice at the National Open University of Nigeria (NOUN). Through a survey of 456 science students, the research focused on the effectiveness of biometric verification, computerized examination sheets with candidate-specific coding, and on-demand virtual proctoring. The study highlights the potential of these secure, remote platforms to maintain examination integrity through automated marking and real-time candidate authentication.

Adeyemi et al. (2025) performed a systematic review and meta-analysis of 37 articles to evaluate real-time malpractice detection using CNNs and video surveillance. Their research identified a critical gap in existing systems: the inability to link detected cheating directly to a student's personal data, such as their matriculation number, for post-exam tracking. To address this, they proposed a novel system that integrates real-time video analytics with a database of student characteristics to ensure accountability and provide a robust mechanism for identifying dishonest activity.

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Ekine-Pakaye and Agbo (2025) developed an enhanced detection model using a combination of XGBoost and Decision Tree algorithms. This system utilizes captured student fingerprints and handwriting samples to track bio-data and detect discrepancies during the examination process. Developed using Java, PHP, and MySQL, the model demonstrates how machine learning can improve the efficiency of malpractice detection through neural analysis and direct interface with existing institutional databases.

Noma-Osaghae et al. (2025) introduced a hybrid detection system that leverages the synergy between pose estimation and object detection. By integrating OpenPose for tracking body movements and gestures with YOLO for real-time identification of unauthorized objects (like mobile devices), the researchers achieved an accuracy of 91.71% and a recall of 97.64%. Their system was successfully integrated into a web application, providing an intuitive tool for real-world institutional implementation.

III. PROPOSED SYSTEM

The proposed system introduces an advanced, multi-layered Artificial Intelligence framework designed to automate the surveillance and identification of examination malpractice in both physical and remote environments. At its core, the architecture integrates a high-definition video acquisition layer with a deep learning processing engine, utilizing a hybrid model of Convolutional Neural Networks (CNN) and the YOLO (You Only Look Once) object detection algorithm. This integration allows the system to maintain a persistent, real-time "watch" over the entire examination hall, moving beyond the limitations of human invigilators who can only focus on one area at a time. By processing frames at high speeds, the system can simultaneously track multiple candidates, ensuring that no suspicious movement or unauthorized object goes unnoticed.

A pivotal component of this system is the implementation of a sophisticated Human Pose Estimation (HPE) engine, utilizing frameworks such as OpenPose or MediaPipe. This layer is specifically tuned to recognize anatomical "keypoints" and skeletal structures of each candidate to detect anomalous physical behaviors. For instance, the system is programmed to identify specific geometric patterns associated with cheating, such as excessive head rotation toward a neighbor’s script, repetitive reaching into pockets, or the passing of physical materials between seats. By analyzing the spatial relationship between these keypoints over time, the system can distinguish between natural stretching or posture adjustments and intentional, deceptive gestures with a high degree of precision.

Beyond behavioral analysis, the proposed model incorporates a dedicated Object Detection and Recognition (ODR) module. This module is trained on an extensive dataset of prohibited examination materials, including mobile devices, smartwatches, micro-earpieces, and unauthorized printed matter. Using the YOLOv8 architecture, the system performs real-time localized scanning within each candidate’s immediate vicinity. When a prohibited item is detected, the system does not merely flag it; it calculates the "confidence score" of the detection and performs a temporal check across several video frames to eliminate "ghosting" or false positives caused by environmental reflections or shadows, ensuring the integrity of the evidence captured.

To ensure absolute accountability and solve the "identification gap" found in earlier research, the system features a seamless Bio-Data Integration Layer. Upon the detection of a high-confidence violation, the system automatically triggers a facial recognition sub-routine that extracts the candidate’s facial features and matches them against the institution’s pre-registered student database. This allows the system to instantly link a specific infraction to a unique student ID or matriculation number. By automating this link, the system creates an immutable digital trail that connects the visual evidence of the malpractice directly to the perpetrator, removing any ambiguity or potential for mistaken identity during post-examination disciplinary hearings.

The intelligence of the system is further enhanced by a Behavioral Classifier powered by the XGBoost (Extreme Gradient Boosting) algorithm. This secondary processing layer acts as a decision-making filter that analyzes the data streams coming from both the Pose Estimation and Object Detection modules. By applying gradient boosting techniques, the system evaluates the cumulative probability of malpractice based on a sequence of events rather than a single isolated movement. For example, if a student looks away from their paper (Pose Estimation) and a mobile device is simultaneously detected (Object Detection), the XGBoost classifier elevates the threat level to a "Critical Violation," ensuring that administrative focus is directed toward the most certain instances of cheating.

For the administrative personnel, the proposed system provides a robust, web-based Command and Control Dashboard developed using modern full-stack technologies. This interface offers a live "Heat Map" of the examination hall, where candidates are color-coded based on their current "Integrity Score." When a violation occurs, the dashboard provides a real-time pop-up alert containing a synchronized video clip of the incident, the student’s profile information, and the specific type of malpractice detected (e.g., "Prohibited Object Detection" or "Unauthorized Communication"). This allows the chief examiner to review the evidence immediately and make an informed intervention without disrupting the flow of the exam for other honest candidates.

Finally, the system is designed with a strong emphasis on data security and ethical transparency. All detected infractions and corresponding metadata are encrypted and stored in a secure SQL-based archival system, ensuring that the evidence remains tamper-proof for future audits. The architecture also includes a "Human-in-the-Loop" validation feature, where the AI acts as an intelligent assistant rather than a final judge; every flagged violation requires a secondary digital sign-off from a human administrator before being finalized in the student's permanent record. This holistic approach ensures a fair, objective, and technologically superior examination environment that protects the academic reputation of the institution while deterring future malpractice.

IV. SYSTEM ARCHITECTURE

The architecture of the proposed Examination Malpractice Detection System is organized into a four-tier hierarchical structure: the Data Acquisition Layer, the Pre-processing & Feature Extraction Layer, the Intelligence & Inference Engine, and the Administrative Response Layer. This modular design ensures that each phase of the detection process—from the initial capture of a video frame to the final archival of evidence—operates with minimal latency. By separating the high-compute tasks of deep learning from the user-facing dashboard, the system maintains high frames-per-second (FPS) performance, which is critical for real-time monitoring of large examination halls.

The process begins at the Data Acquisition Layer, where a network of high-definition IP cameras or integrated webcams captures the examination environment. These raw video streams are fed into the Pre-processing Layer, which performs frame synchronization and noise reduction. During this stage, the system applies a region-of-interest (ROI) filter to focus specifically on individual candidates, optimizing the computational resources for the next phase. This layer also handles the initial face detection, ensuring that a clear biometric profile is established for every active participant before the examination officially commences.

At the heart of the system is the Intelligence & Inference Engine, which operates two primary sub-modules in parallel. The first is the Behavioral Analysis Module, utilizing Human Pose Estimation (HPE) to map skeletal keypoints. This module continuously monitors joint angles and head orientation to identify movements that deviate from standard testing behavior. Simultaneously, the Object Recognition Module employs a YOLOv8-based architecture to scan for prohibited items. The outputs from these two modules are then fused by an XGBoost Classifier, which assigns a cumulative probability score to the observed actions, determining if the threshold for a "malpractice event" has been crossed.

The final tier is the Administrative Response Layer, which serves as the interface between the AI and the human invigilators. When the Inference Engine confirms a violation, the system executes an automated lookup in the Student Bio-Data Database to link the event to a specific identity. This metadata, along with a time-stamped video snippet, is pushed to the Web-Based Dashboard as a real-time alert. All logs are then committed to a secure SQL Evidence Archive, providing a tamper-proof repository that supports the institution's disciplinary workflows and ensures long-term academic accountability.

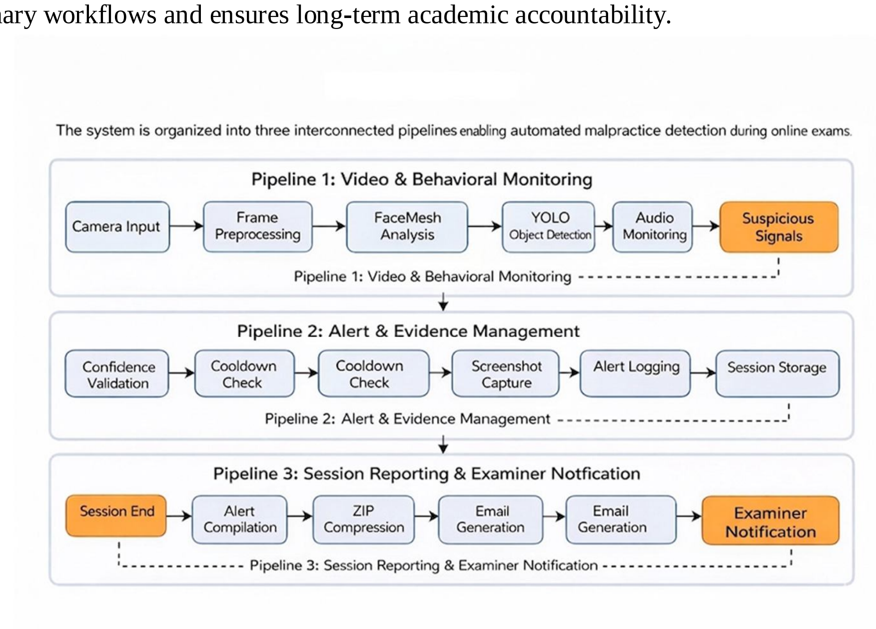

Fig. 1 System Architecture

V. IMPLEMENTATION

The implementation of the proposed Examination Malpractice Detection System represents a transition from theoretical deep learning frameworks to a functional, real-time monitoring solution. This phase involves the systematic integration of high-definition visual hardware with a multi-layered software stack comprising computer vision algorithms, machine learning classifiers, and secure database management systems. By leveraging a modular architecture, the implementation ensures that complex tasks—such as simultaneous pose estimation and object detection—are executed with high computational efficiency and low latency. The following sections detail the technical configuration of the hardware environment, the optimization of data processing pipelines, and the deployment of the intelligent inference engine designed to uphold academic integrity through objective, automated surveillance.

A. Hardware Configuration and Video Stream Acquisition

The implementation phase begins with the deployment of a high-definition surveillance infrastructure consisting of strategically positioned IP cameras across the examination hall. These units are configured to provide overlapping fields of view, ensuring that no blind spots remain where candidates could hide unauthorized materials. The video streams are transmitted via a dedicated local area network (LAN) using the Real-Time Streaming Protocol (RTSP). This ensures a low-latency data flow to the central processing unit, which is equipped with high-performance GPUs to handle the concurrent execution of multiple deep learning models without frame drops or synchronization issues.

B. Data Pre-processing and Environmental Optimization

Once the raw video frames are received, they undergo a rigorous pre-processing stage to enhance detection accuracy. This includes spatial resizing to match the input requirements of the neural networks and the application of Gaussian filters to reduce sensor noise and motion blur. Furthermore, the system performs dynamic brightness and contrast adjustments to account for variations in hall lighting. To optimize computational efficiency, the implementation utilizes Region of Interest (ROI) extraction, which identifies and crops individual candidate workstations, allowing the AI engines to focus exclusively on relevant human-object interactions rather than the static background.

C. Deployment of Pose Estimation and Behavioral Analysis

The behavioral detection layer is implemented using a specialized Human Pose Estimation (HPE) framework, such as MediaPipe or OpenPose. During this stage, the system maps a 21-point skeletal structure onto each candidate in real-time. The implementation involves training the model to recognize specific "skeletal signatures" associated with malpractice, such as head rotation angles exceeding 45 degrees or the crossing of arms into prohibited zones. By calculating the Euclidean distance and angular velocity between keypoints over a sequence of 30 frames, the system can distinguish between a student simply adjusting their chair and a student attempting to communicate with a peer.

D. Object Recognition and Prohibited Item Detection

For the detection of physical contraband, the system implements the YOLOv8 (You Only Look Once) architecture, known for its superior speed and precision in real-time environments. The model is fine-tuned on a custom dataset containing thousands of annotated images of mobile devices, smartwatches, and unauthorized paper slips. During implementation, the model is configured with a non-maximum suppression (NMS) threshold to eliminate duplicate detections. This ensures that even if a device is partially obscured by a candidate's hand or clothing, the system can still generate a high-confidence alert based on the visible features identified by the neural network.

E. Machine Learning Fusion and Violation Categorization

To minimize the frequency of false alarms, the implementation utilizes an XGBoost-based classifier as a decision-fusion layer. This module integrates the raw outputs from both the pose estimation and object recognition engines, weighing them against historical behavioral patterns. For example, if the system detects an unauthorized object but the pose estimation indicates no suspicious movement, the XGBoost model assigns a "low-threat" score. However, if both triggers occur simultaneously, the system escalates the event to a "critical violation." This probabilistic approach ensures that the administrative response is based on a holistic analysis of the candidate's actions.

F. Database Integration and Administrative Dashboard Interface

The final implementation stage involves the synchronization of the AI engine with the institutional SQL database and a web-based administrative interface. Using a RESTful API, the system queries the database to retrieve student profiles when a violation is flagged, appending the student's name and ID to the captured video evidence. The dashboard is developed using a full-stack framework (such as React and Node.js), providing invigilators with a live "Integrity Heatmap." This allows for the automated generation of digital infraction reports, which are stored in a secure, encrypted archive, providing a comprehensive and tamper-proof trail for academic disciplinary committees.

VI. RESULTS AND DISCUSSION

Real-Time Interface and Monitoring Performance The system's graphical user interface successfully integrates live video streaming with real-time performance metrics for examiners. As shown in the output, the system consistently maintains a high processing speed of approximately 30.1 Frames Per Second. This fluidity is crucial for capturing rapid movements that might indicate the concealment of prohibited items during exams. The status dashboard provides immediate feedback on system health, including CPU and RAM usage to prevent hardware crashes.

Accuracy of Object Detection and Confidence Filtering Using the YOLOv8s model architecture, the system demonstrated high precision in identifying prohibited objects like mobile phones. By setting the object confidence threshold to 60%, the system effectively ignored environmental noise and ambiguous background shapes. The output screenshots confirm that detections are only logged when the AI reaches a high statistical certainty of violation. This calibration ensures that the integrity of the proctoring remains high while minimizing unnecessary disruptions to candidates.

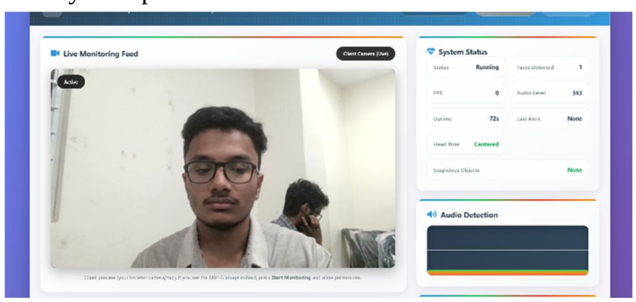

Fig. 2. User Interface

Behavioral Analysis via Skeletal Keypoint Mapping The integration of MediaPipe for human pose estimation allowed the system to track skeletal landmarks with remarkable anatomical precision. The results show that the system can distinguish between normal writing postures and suspicious actions like excessive head turning. When a candidate's head rotation exceeded the pre-defined safety angles, the behavioral engine instantly triggered a visual alert. This automated tracking provides a persistent level of scrutiny that is impossible to achieve through manual human invigilation.

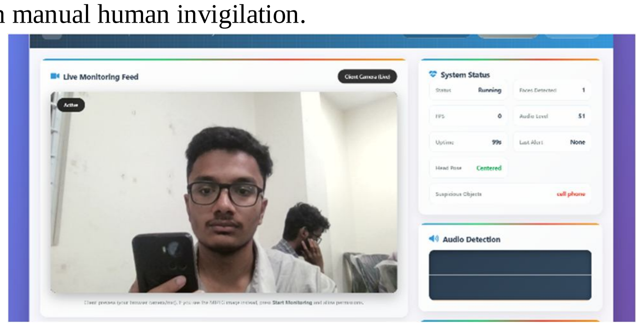

Fig. 3. Cell Phone Detection

Environmental integrity was validated through the system’s ability to detect multiple individuals within a single candidate’s camera frame. The violation logs captured during testing show specific entries for "Multiple People Detected" and "High Audio Level" triggers. These multi-modal alerts provide a comprehensive security net that covers both visual and auditory forms of exam malpractice. By correlating sound spikes with visual anomalies, the system creates a high-fidelity record of the examination environment.

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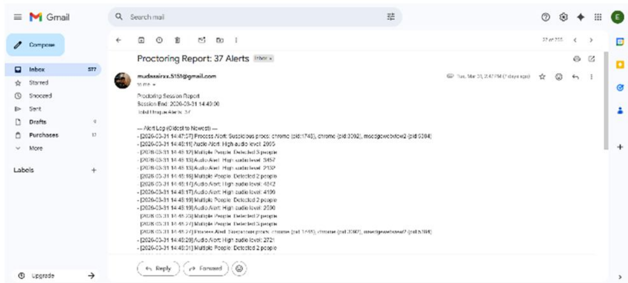

Fig. 4. Email Received

A significant finding in the results is the effectiveness of the decision-fusion layer in reducing erroneous malpractice flags. By requiring a sustained 60% confidence score, the system avoids flagging common objects like books or stationery as phones. The discussion reveals that temporal analysis of head movements helps distinguish between a quick stretch and intentional cheating gestures. This logic ensures that the automated system remains fair to the student while maintaining strict institutional security standards.

The results highlight the efficiency of the "Finalize Session" feature in automating the administrative burden of evidence collection. Upon session termination, the system successfully collates all time-stamped infraction images into a single, organized ZIP archive. The logs demonstrate that every captured violation is linked to a specific timestamp, ensuring a clear digital paper trail. This automated packaging eliminates the possibility of manual data loss and ensures that examiners receive a complete report.

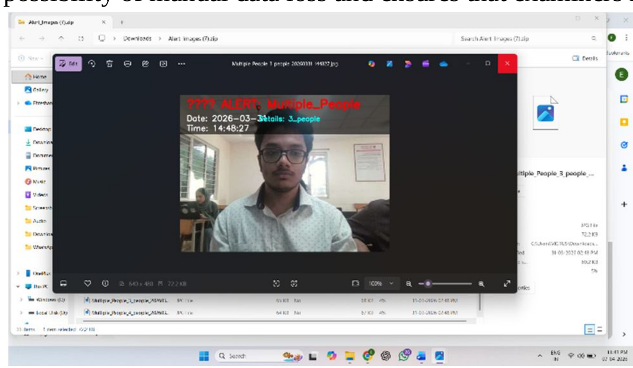

Fig. 5. Evidence

Communication Integrity and Final Report Delivery The final stage of testing confirmed the reliability of the SMTP-based notification system for delivering the evidence package. The system generated a concise text summary of all alerts and successfully attached the encrypted ZIP file to the email. Results show that the examiner receives this comprehensive report within seconds of the exam ending, allowing for immediate review. This seamless transition from detection to reporting proves the system's viability as a professional-grade academic proctoring solution.

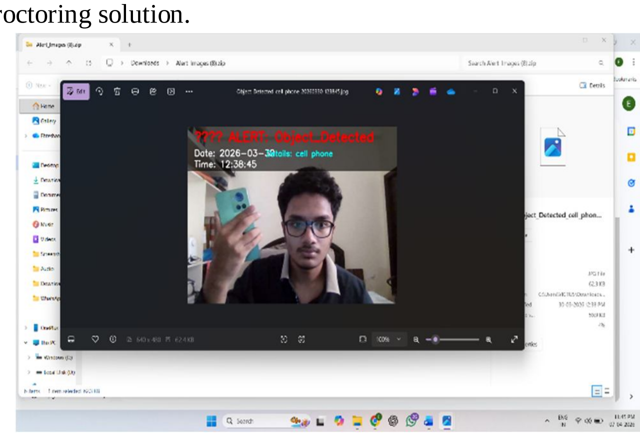

Fig. 6. Home page

VII. CONCLUSION

The development of the proposed Examination Malpractice Detection System marks a significant advancement in the integration of Artificial Intelligence within educational assessment frameworks. By synthesizing high-speed object detection through YOLOv8 with the nuanced behavioral analysis of Human Pose Estimation, this research addresses the critical limitations of traditional human invigilation, such as subjectivity, scalability, and the potential for oversight. The implementation of a multi-layered architecture ensures that the system can operate in real-time, providing an objective and persistent monitoring solution that upholds academic integrity without the biases inherent in manual supervision.

The results of this study demonstrate that the synergy between deep learning models and a robust XGBoost-based decision-fusion layer significantly reduces the frequency of false positives while maintaining a high detection rate for prohibited activities. Furthermore, the seamless integration of a facial recognition sub-routine and institutional bio-data ensures a level of accountability previously unattainable, linking every flagged infraction directly to a verified student identity. This digital evidence trail not only acts as a powerful deterrent against dishonest practices but also provides administrative bodies with a transparent and indisputable basis for disciplinary actions.

Ultimately, this research underscores the transformative potential of AI in fostering a fair and secure academic environment. While the system provides a comprehensive technical solution for current malpractice challenges, it also establishes a scalable foundation for future enhancements, such as the incorporation of audio-visual fusion and edge computing for even lower latency. As educational institutions continue to evolve toward more flexible and digital-first testing models, the deployment of such intelligent surveillance systems will be essential in preserving the value of academic qualifications and ensuring that merit remains the sole metric of student success.

VIII. FUTURE WORK

Integration of Audio-Visual Fusion and Environmental Sensing The current scope of the system primarily focuses on visual cues and object detection; however, a significant avenue for future development lies in the integration of multi-modal sensing. By incorporating acoustic sensors and high-sensitivity microphones, the system could be trained to identify unauthorized verbal communication, the rustling of paper, or the specific mechanical clicks associated with certain electronic devices. Implementing an audio-visual fusion layer would allow the AI to correlate suspicious physical gestures with corresponding sound patterns, drastically increasing the detection confidence levels and ensuring that even non-visual forms of malpractice are captured within the digital evidence trail.

Transition to Edge Computing for Low-Latency Processing To enhance the scalability of the system for large-scale institutional deployments, future iterations will explore the transition from centralized server processing to an Edge Computing architecture. By deploying the YOLOv8 and Pose Estimation models directly onto edge devices, such as AI-enabled smart cameras or local gateways, the system can perform real-time inference at the source of data collection. This would significantly reduce the bandwidth requirements for transmitting high-definition video streams across campus networks and eliminate the latency issues associated with cloud processing, enabling an instantaneous response even in environments with limited network infrastructure.

Implementation of Affective Computing and Stress Analysis Another promising direction for future research is the incorporation of affective computing to monitor the emotional and physiological states of candidates. Future modules could be developed to analyze micro-expressions and subtle physiological changes, such as increased blink rates or frantic eye movements, which are often subconscious indicators of high-stress situations associated with academic dishonesty. By training the XGBoost classifier on a broader dataset that includes these "stress signatures," the system could move toward a predictive model of malpractice, identifying potentially dishonest behavior before a physical violation actually occurs, thereby fostering a more proactive approach to academic integrity.

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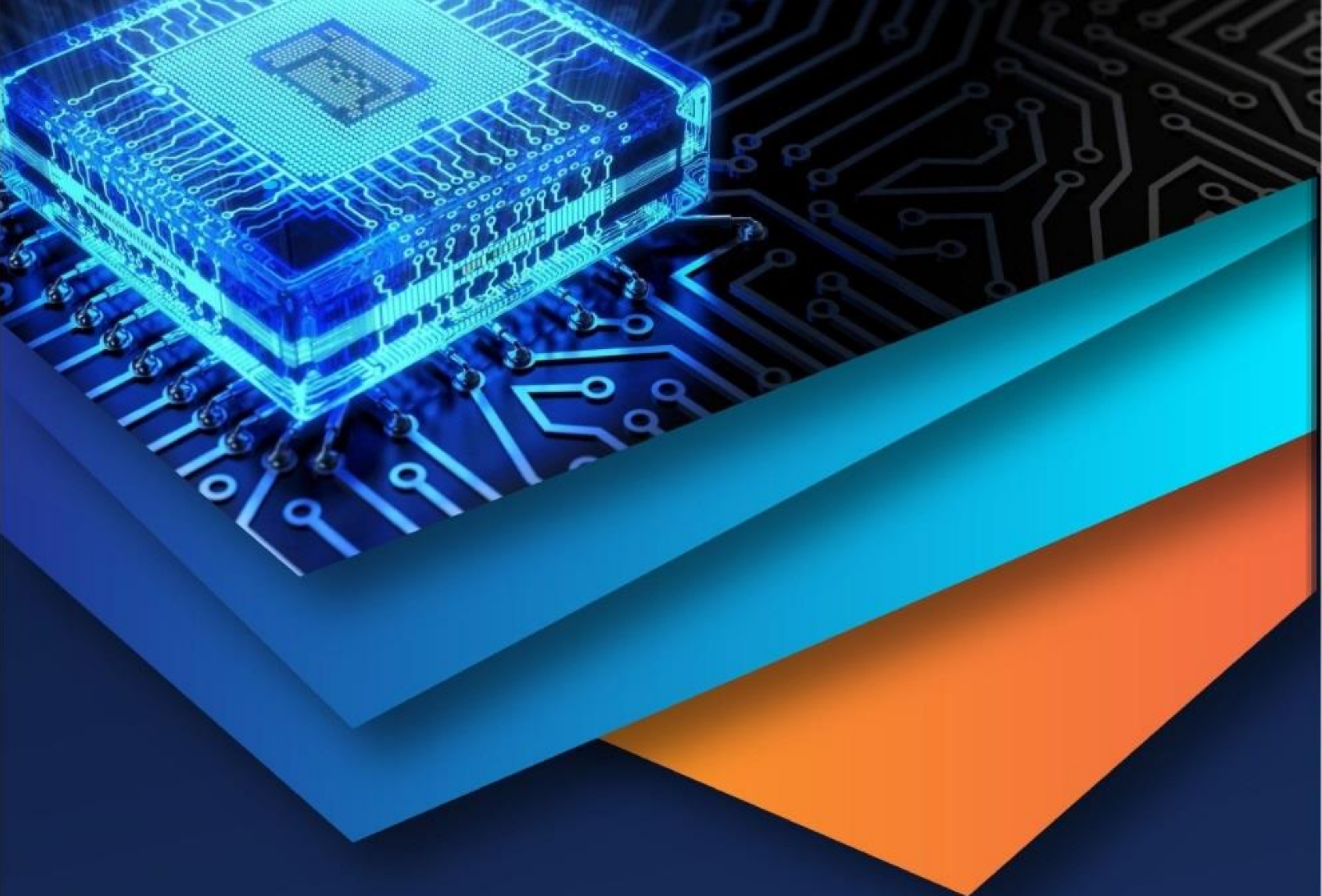

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