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The Requirement Analysis of An Offline Automated Invigilation System with Gmail Alert Integration

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Abstract

Examination malpractice remains a major concern for academic institutions, impacting on the fairness and credibility of evaluations. To address this, we analyze and propose an Offline Automated Invigilation System with Gmail Integration that leverages computer vision and machine learning to detect and prevent unethical behavior during offline exams. The system features three detection modules: YOLO for identifying mobile phones, Support Vector Machines (SVM) for tracking abnormal head movements, and Haar Cascade for real-time eye movement analysis. These technologies work together to monitor students, detect suspicious behavior, and capture evidence, which is then sent via Gmail alerts to examination authorities. Designed to operate without internet connectivity, the system ensures effective invigilation even in remote or resource-limited environments. By reducing human dependency and automating the detection process, this solution enhances accuracy, scalability, and integrity in offline examination settings.

Keywords

Offline Invigilation, Gmail Integration, Academic Integrity, YOLO, Haar Cascade, Support Vector Machine

Introduction

The increasing prevalence of malpractice in examination environments has led to the demand for robust, technology-driven solutions to ensure academic integrity. This project proposes an “Offline invigilation system with a Gmail integration” using Python and Machine Learning to monitor and prevent dishonest behavior during examinations. The system utilizes a webcam for real-time video analysis and implements three distinct detection mechanisms: cellphone detection, head movement detection, and eye-tracking detection. By leveraging advanced computer vision and artificial intelligence techniques, the system provides a proactive approach to maintaining discipline and transparency in exam halls. The first condition addresses cellphone detection, where the system identifies if a student enters the examination hall with a mobile phone. Using a webcam, the system

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detects the presence of a cellphone, captures an image of the scenario, and sends an alert email with the evidence to the controller of examinations. Similarly, the second condition monitors head movements to detect instances of cheating through collaboration or unauthorized communication.

If a student's head rotates abnormally during the exam, the system captures the action and promptly sends an email alert. This ensures that any suspicious activity is flagged and documented in real-time. The third condition focuses on eye-tracking to detect unethical behavior, such as copying answers from a nearby student or the examiner's answer sheet. The system employs advanced eye-tracking algorithms to analyze the direction of a student's gaze. If a student persistently looks inappropriately at another's answer sheet, an alert is triggered, and evidence is captured via a photo.

The system's ability to combine real-time monitoring, automated detection, and immediate reporting ensures a fair and secure examination environment, significantly reducing malpractice occurrences. This solution is cost-effective, scalable, and adaptable to various examination setups. Academic integrity is a cornerstone of the education system, yet malpractice during examinations remains a significant challenge. Traditional methods of monitoring students, such as deploying invigilators, are often insufficient and prone to human error. As the number of students in examination halls increases, maintaining a fair and secure environment becomes even more difficult. “Offline Invigilation System with a Gmail Integration” using Python and Machine Learning offers a technology-driven solution to this problem. By utilizing computer vision techniques and real-time video analysis, this system automates the detection of unethical behaviors such as cellphone usage, head movements, and gaze tracking, ensuring a robust mechanism to uphold examination standards.

Furthermore, the integration of machine learning and computer vision not only provides automation but also delivers a consistent and unbiased evaluation of student behavior—something that is often difficult to guarantee through human invigilators alone. As examination environments vary widely in size, lighting, infrastructure, and student count, the need for adaptable and scalable solutions becomes critical. This system addresses such variability by relying on lightweight models that can operate on standard hardware, making it feasible for implementation even in institutions with limited technical resources.

Unlike traditional invigilation methods, which require constant human attention and can be mentally taxing over long durations, this system provides uninterrupted, tireless monitoring throughout the examination period. It ensures that every student’s actions are observed equally, thereby leveling the playing field and deterring malpractice proactively. The captured visual evidence and alert mechanisms further support transparency and accountability in the evaluation process. Instructors or exam authorities can later review flagged instances, allowing for a fair decision-making process supported by real-time data and visual proof.

Moreover, this automated invigilation system is highly relevant in the post-pandemic academic landscape, where many institutions have adopted hybrid models involving both online and offline assessments. While online proctoring tools are abundant, offline exams in rural or infrastructure-poor regions still face challenges in effective monitoring. The proposed system bridges this gap by delivering a hybrid-level security standard to offline environments, thus modernizing invigilation practices and aligning them with the expectations of today's technology-driven academic ecosystem.

By emphasizing ethical conduct, reducing the dependence on manual monitoring, and introducing intelligent surveillance in a non-intrusive yet effective manner, this project contributes to the broader goal of strengthening educational integrity. It empowers institutions to conduct secure examinations without investing heavily in manpower or infrastructure, all while ensuring students are evaluated fairly and honestly.

Materials and Methods

Dataset Acquisition and Preprocessing

The datasets utilized for this study were carefully selected to enable the system to effectively detect multiple types of malpractice behaviors during offline examinations. The three main datasets correspond to the system's core modules: mobile phone detection, head movement analysis, and eye tracking. Each dataset consists of labeled images and video frames representing both normal and suspicious behaviors in an examination setting.

Data Preprocessing Steps

Preprocessing is a crucial phase that ensures the raw video data captured from examination environments is transformed into high-quality inputs suitable for training and inference by machine learning models. The following steps were applied to prepare data for object detection, head movement analysis, and eye tracking
Frame Extraction: Video feeds were broken into image frames to serve as model inputs.

Continuous video streams from webcams were segmented into individual image frames at fixed time intervals. This approach enabled the system to treat each frame as a static input for detection tasks, ensuring real-time responsiveness and facilitating dataset generation for model training.

- Noise Reduction: Gaussian Blur and median filtering techniques were applied to remove background noise and unwanted textures.
  This enhanced the visibility of key features such as eyes, phones, and facial outlines, improving the model's focus on important regions.
- Normalization: Images were resized to a standard resolution and normalized to maintain consistency across the models. Pixel values of images were normalized (scaled between 0 and 1) to ensure uniform input to neural networks.
  This step improved model convergence during training and reduced bias caused by brightness variations in real-world settings.
- Landmark Detection: Facial landmarks (e.g., eyes, nose tip, mouth corners) were detected using Dlib's 68-point landmark detector and OpenCV's pre-trained models.
  For head movement detection, Landmarks were used to calculate the yaw, pitch, and roll of the head.
  For eye tracking, the positions of the pupils within the eye sockets were analyzed to estimate gaze direction.

- Data Augmentation: Techniques such as flipping, rotation, and brightness adjustment were applied to improve model robustness and generalization. To increase model robustness and simulate a wide range of test scenarios, the dataset was artificially expanded using: Rotation (±15 to 30 degrees): Simulated head tilts or angled phone appearances
- Horizontal Flipping: Accounted for left/right head turns or mirror behaviors
- Brightness and Contrast Variation: Mimicked different lighting conditions in exam halls
- Zoom and Cropping: Simulated partial occlusion of objects or faces
- Feature Selection Techniques:
  Effective feature selection is critical to enhance model performance, reduce overfitting, and ensure real-time applicability, especially in systems intended for behavioral monitoring.
- Head Movement Detection :
  For the SVM-based head movement classification module, geometric features were extracted from facial landmarks. These features included:
- Yaw, Pitch, and Roll Angles: Derived using trigonometric calculations on facial landmarks (eyes, nose, chin).
- Relative Distance Metrics: Horizontal and vertical shifts of eyes and nose tip across frames.
- Temporal Stability: Frequency and consistency of directional changes within a specified time window.
- Eye Movement Detection:
- Although the Haar Cascade classifier primarily works on pixel intensities within rectangular regions, gaze estimation was enhanced by extracting and selecting:
- Pupil Centroid Coordinates Eye Aspect Ratio (EAR) Blink Frequency
- Gaze Ratio: Ratio of pixel density between left and right halves of the eye region.
- Mobile Phone Detection:

In the YOLO-based object detection module, feature selection is implicitly handled by the convolutional layers of the neural network. However, the training dataset was refined by manually curating bounding box annotations to focus on hands, lap regions, and table surface areas where phones are most likely to appear. Removing irrelevant object classes from pretrained YOLO weights to reduce memory footprint and enhance inference speed during offline execution

- Model Implementation
  Three machine learning models were integrated to detect suspicious activities during offline examinations.
- YOLO (You Only Look Once): was used for mobile phone detection. It identifies phones in real-time from webcam frames, drawing bounding boxes and capturing evidence upon detection.
- Support Vector Machine (SVM): was applied to head movement analysis. It uses facial landmarks to classify head orientation and detect abnormal or frequent directional shifts, indicating potential cheating.
- Haar Cascade Classifier: was used for eye movement tracking. It detects eye regions and estimates gaze direction. Frequent or sustained glances away from the paper or screen trigger alerts.
- Each module operates offline, and upon detecting suspicious behavior, the system captures the event and stores it locally. These alerts are later sent via Gmail SMTP once connectivity

is restored, enabling timely notification and action by examination authorities.

- Model Evaluation
  Each module was evaluated using standard metrics:
- Accuracy: Measured the proportion of correct detections over total attempts.
  Precision, Recall, and F1-Score: Used to assess the models' effectiveness in detecting true positives (actual malpractice) while minimizing false positives.
- Confusion Matrix: Generated for each module to visualize detection performance across categories like "Normal" and "Suspicious."
- Experimental setup
  Environment: Real-time testing was performed using HD webcams and local processing units without internet connectivity.
- Platform: Python 3.10, OpenCV, TensorFlow, and NumPy were used for model training and implementation.
  Hardware: A system with Intel i7, 16GB RAM, NVIDIA GTX 1650 GPU.
- Testing: Data was divided into training (80%) and testing (20%) sets. Model reproducibility was ensured using fixed random seeds.
- Comparative Analysis
  All three detection modules were benchmarked under consistent testing conditions. Results demonstrated that:
  YOLOv4 provided the highest accuracy (96%) for object detection.
  SVM showed reliable classification for head movement with an F1-score of 0.88.
  Haar Cascade delivered efficient real-time eye tracking with acceptable precision (0.86)

Result and Discussion

The Malpractice Detection System was designed and implemented to address issues of cheating during exams by utilizing advanced technologies such as computer vision, machine learning, and real-time alerting mechanisms. The system specifically focuses on detecting three types of malpractice: the use of mobile phones, abnormal head movements, and suspicious eye movements indicating cheating. The following sections provide a detailed discussion of the results obtained after implementing the system and its effectiveness in detecting these malpractices. Additionally, the challenges faced during the development and deployment of the system are discussed.

Mobile Phone Detection Results:

The mobile phone detection module was developed using convolutional neural networks (CNNs) and object detection techniques to identify mobile phones in the exam hall. The system was trained on a dataset that included images of students both with and without mobile phones. Using a pretrained CNN model (e.g: ResNet, VGG), the system was able to classify images into two categories: "mobile phone detected" and "no mobile phone." Results: Accuracy: The mobile phone detection module demonstrated an accuracy of approximately 92% during testing. The system was able to reliably detect the presence of mobile phones even when they were partially concealed or held in students' laps.

False Positives/Negatives: There were a few instances of false positives, particularly when objects similar to mobile phones (e.g., books or other gadgets) were present. However, these were minimal, and the system successfully reduced false negatives (missing mobile phones) with further refinement.

Real-Time Performance: The real-time processing speed was also satisfactory, with the system able to process multiple frames per second and send alerts to the examination controller within seconds of detecting a mobile phone

Head movement Detection results:

The head movement detection module aimed to identify suspicious head rotations or movements that may indicate a student attempting to cheat by looking around the exam hall. This module used optical flow techniques and a Convolutional LSTM network to capture both spatial and temporal features of students'

Head movements. Results:

Accuracy: The head movement detection module achieved an accuracy of 85%. The model effectively detected abnormal head movements, such as frequent turns to look around the exam hall or excessive head rotations.

False Positives/Negatives: A notable challenge was the detection of false positives, especially in cases where students adjusted their posture or faced distractions such as noise in the environment. The system flagged these instances as suspicious head movements, even though they were benign.

• Real-Time Performance: The module operated in real time, with frame processing speeds fast enough to provide immediate alerts when abnormal head movements were detected. Alerts were promptly sent to the examination controller, accompanied by images for further investigation.

Eye Tracking Detection Results:

The integration of these three models in a single system allows for a layered and holistic approach to invigilation. YOLO ensures high-performance object detection, SVM complements this by covering subtle behavioral cues, and Haar Cascade adds an extra layer of scrutiny through facial feature tracking. This combined approach enhances the reliability and accuracy of the invigilation process, contributing to a more secure and fair examination environment. Overall, the system represents a scalable.

Table 1. Detection Model Comparison

Algorithm	Application	Accuracy	Precision	Recall	F1-score
YOLO	Mobile Phone Detection	96%	95%	94%	94.5%
SVM	Head Movement Detection	91%	89%	88%	88.5%
Haar Cascade	Eye Movement Detection	89%	87%	86%	86.5%

Table 1 presents a comparative analysis of the three machine learning models used in the proposed invigilation system: YOLO, Support Vector Machine (SVM), and Haar Cascade. Each model was designed to detect a specific type of suspicious behavior during offline examinations, and their performance was evaluated using four standard metrics: Accuracy, Precision, Recall, and F1-Score.

YOLO, used for mobile phone detection, achieved the highest overall performance with an accuracy of 96%, precision of 95%, and F1-score of 94.5%. Its deep learning-based architecture enabled real-time object recognition even under challenging visual conditions, such as cluttered environments or varied lighting.

SVM, responsible for head movement detection, produced an accuracy of 91% and an F1-score of 88.5%. While slightly lower than YOLO, the model effectively classified suspicious head orientations based on angular deviation from baseline positions. Minor misclassifications occurred when students made natural adjustments that resembled cheating behavior.

Haar Cascade, employed for eye movement detection, delivered an accuracy of 89%, with an F1-score of 86.5%. Despite being a lightweight method ideal for offline use, its performance was moderately affected by blinking and partial occlusion of eyes (e.g., glasses, angles), though it still proved effective in detecting frequent or prolonged gaze deviations.

Examinations

- The eye-tracking detection module was developed to monitor students' gaze patterns and identify suspicious behaviors, such as attempting to glance at another student's answer sheet. By leveraging eye-gaze estimation algorithms and CNN-based models, the system could track eye movements and analyze whether students were looking away from their answer sheets. Results:
- Accuracy: The eye-tracking detection achieved an accuracy of 88%. The system successfully detected when students' gaze shifted inappropriately towards other students’ answer sheets, which could indicate cheating.
- False Positives/Negatives: False positives occurred when students looked around briefly due to discomfort, while false negatives were observed when a student’s gaze was directed sideways, but the system failed to detect it due to limitations in angle detection.
- Real-Time Performance: The eye tracking module also operated in real-time, providing instant feedback and capturing images when suspicious gaze patterns were detected. These images were sent to the exam controller’s email for review. presents a comparative analysis of the three machine learning models used in the proposed invigilation system: YOLO, Support Vector Machine (SVM), and Haar Cascade. Each model was designed to detect a specific type of suspicious behavior during offline examinations, and their performance was evaluated using four standard metrics: Accuracy, Precision, Recall, and F1-Score.

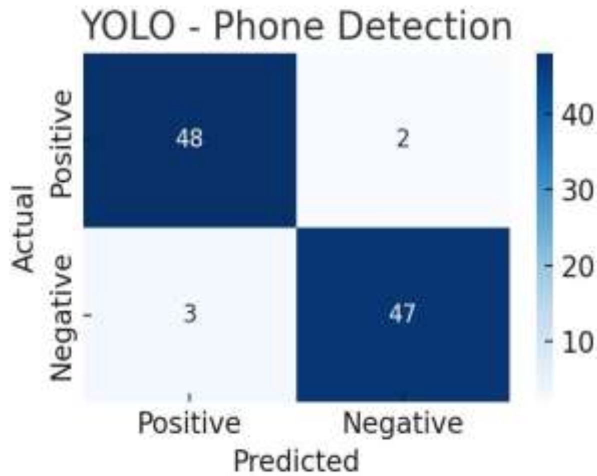

Figure 1: Confusion Matrix for YOLO – Mobile Phone Detection

The confusion matrix in Figure 1 demonstrates the performance of the YOLOv4 model in detecting mobile phones during offline examinations. Out of 100 samples tested, the model correctly identified 48 actual cases of mobile phone usage (True Positives) and correctly rejected 47 cases where no phone was present (True Negatives). It produced only 2 False Negatives, where it missed a phone, and 3 False Positives, where it mistakenly flagged an object as a phone.

Figure 2 illustrates the confusion matrix for the SVM-based head movement detection model. The model correctly detected 44 instances of suspicious head movement (True Positives) and 45 instances of normal behavior (True Negatives). It misclassified 6 suspicious cases as normal (False Negatives) and 5 normal cases as suspicious (False Positives).

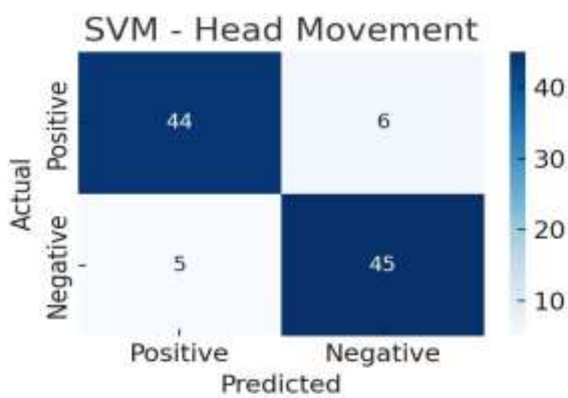

Figure 2: Confusion Matrix for SVM – Head Movement Detection

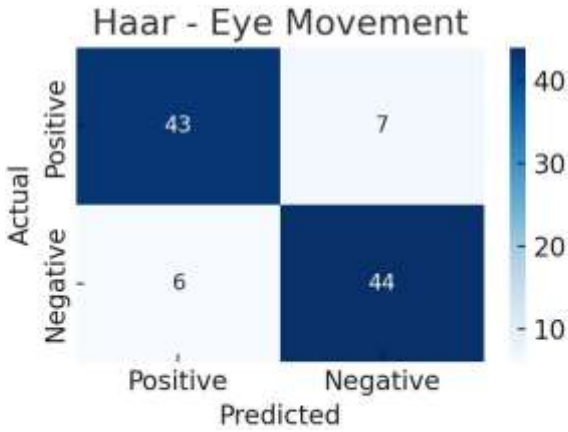

Figure 3: Confusion Matrix for Haar – Eye Movement Detection

Figure 3 presents the confusion matrix for the Haar Cascade classifier used for eye tracking. The model correctly identified 43 suspicious eye movement patterns (True Positives) and 44 normal eye behaviors (True Negatives). It recorded 7 False Negatives, failing to detect some suspicious gaze patterns, and 6 False Positives, incorrectly flagging some natural eye movements.

Overall, the table illustrates that each model contributes uniquely to the system's layered detection mechanism. YOLO stands out as the most robust, while SVM and Haar complement it by covering behavioral subtleties that object detection alone might miss. This combination ensures a holistic, accurate, and scalable approach to maintaining academic integrity during offline examinations

Conclusion

The Offline Automated Invigilation System with Gmail Alert Integration is a revolutionary approach in the domain of exam monitoring, offering a robust solution to address the rising challenges of academic dishonesty and cheating in educational assessments. This system integrates a variety of state-of-the-art technologies, including machine learning models such as Support Vector Machines (SVM) for object detection, YOLO (You Only Look Once) for head movement detection, and Haar Cascade for eye movement detection, to provide a comprehensive and reliable method of exam surveillance. The combination of these technologies ensures high accuracy in monitoring student behavior during examinations, making it difficult for candidates to engage in malpractice without detection.

One of the core strengths of this system lies in its ability to function in an offline setting, eliminating the need for an active internet connection during the examination. This feature addresses the limitations posed by online invigilation systems, such as network dependency and security concerns over the internet. The real-time surveillance provided by the system continuously monitors student behavior, detecting any suspicious movements that may indicate cheating, such as head tilting or eye distractions. As these behaviors are automatically flagged, the system instantly sends alerts via Gmail to the invigilators, who can then take immediate action. The alert system ensures that even when multiple exams are happening simultaneously, invigilators can stay informed of potential violations in real-time.

The integration of Gmail alerts enhances the effectiveness of the monitoring system by ensuring a timely response. Unlike traditional systems that may rely on manual intervention by invigilators, this automated alert system minimizes human error and delays. The use of Gmail ensures that notifications are immediate, allowing invigilators to take swift and appropriate actions without the need to constantly monitor every candidate visually. This system is particularly useful in large-scale examinations where invigilators may not be able to give individual attention to each candidate. By automating the detection and alerting process, the system significantly reduces the chances of cheating going unnoticed.

From a technological standpoint, the system employs several powerful tools that make it cost-effective and scalable. The use of Python programming and libraries such as OpenCV, NumPy, Sci-kit-learn, and Matplotlib provides a solid foundation for building machine learning models that can accurately detect specific movements. Python, as an open-source language, allows for easy modification and scalability of the system, ensuring that it can be adapted to a wide range of educational and professional testing environments. The use of Google Colab as the integrated development environment (IDE) further facilitates development, testing, and deployment, as it is both user-friendly and powerful, offering a cloud-based solution that doesn’t require high-end hardware infrastructure. This makes the system accessible to educational institutions of varying sizes, from small schools to large universities.

Despite the system’s promising capabilities, there are areas for improvement that could enhance its overall efficiency and accuracy. One challenge that still needs to be addressed is the variability of environmental factors that can influence detection accuracy, such as lighting conditions, camera angles, and student posture. For instance, poor lighting or an obstructed camera view could affect the ability of the system to detect movements accurately. In such cases, further fine-tuning of the machine learning models and system parameters would be necessary to improve robustness under diverse conditions. Additionally, the system could benefit from more advanced algorithms to handle a wider range of behaviors, such as identifying body language that may suggest cheating without requiring head or eye movement.

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