Real-Time Integrity Monitoring in Online Exams Using Deep Learning Model

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Abstract: The rapid shift towards online education and remote assessments has intensified the challenge of ensuring academic integrity. This research presents a comprehensive integrity monitoring called as cheat detection system utilizing the YOLOv8 model, a state of art deep learning model designed to enhance the credibility of online examinations. Our system employs a live video feed from a webcam to monitor examinees or individuals taking an examination in real-time, detecting multiple persons, unauthorized gadgets (such as mobile phones, laptops, and headphones), and eye movements indicative of potential cheating. The YOLOv8 model is trained to accurately recognize these objects and behaviors, triggering immediate alerts upon suspicious detection. The research paper details the design, implementation, and evaluation of this system, demonstrating its efficacy in maintaining the integrity of online exams. Our results indicate that the system can significantly reduce cheating incidents, offering a robust solution applicable to educational institutions, certification bodies, and other scenarios requiring stringent monitoring.

1 INTRODUCTION

Cheating in online examinations has emerged as a significant challenge in the digital age, exacerbated by the widespread adoption of remote learning and assessment tools (Nguyen, Rienties, et al. 2020). The integrity of online assessments is frequently compromised by candidates using unauthorized devices, collaborating with others, or employing other deceitful strategies. Various methodologies have been proposed and implemented to mitigate these issues, including traditional proctoring, automated invigilation systems, and advanced AI-driven solutions. Existing works leverage facial recognition, behavior analysis, and object detection to monitor and flag suspicious activities (Krafka, Khosla, et al. 2016), (Chu, Ouyang, et al. 2022). However, these methods often suffer from limitations in accuracy, adaptability, and real-time performance, underscoring the need for more robust and dynamic solutions. In this project, we propose a comprehensive cheat detection system leveraging the YOLOv8 model, renowned for its efficiency in object detection tasks. The system integrates a live video feed from a webcam to monitor examinees in real-time. Our approach focuses on detecting multiple persons in the frame, identifying the presence of gadgets such as mobile phones, laptops, and headphones, and implementing gaze detection to monitor eye movements. The model is trained to recognize these objects and activities with high precision, leveraging a diverse and annotated dataset that includes various cheating scenarios and environments. The system utilizes the YOLOv8 architecture comprising deep learning model due to its capability to perform real-time object detection with minimal latency, making it ideal for live surveillance applications. By incorporating transfer learning techniques, we fine-tuned the YOLOv8 model on our custom dataset to improve its detection accuracy for specific cheating-related objects and behaviors. Additionally, we implemented advanced gaze detection algorithms that analyze eye movements to identify patterns indicative of cheating, such as frequently looking off-screen or towards a concealed note. This is achieved using a combination of convolutional neural networks (CNNs) and eye-tracking methodologies integrated with the YOLOv8 detection framework. The cheat detection system features a real-time alert

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mechanism that overlays alert messages directly on the video frame whenever suspicious behavior is detected. This ensures that invigilators can take immediate action without delay. The alerts are accompanied by bounding boxes and labels that specify the type of detected object or activity, providing clear and actionable information. For comprehensive monitoring, the system supports multi-camera setups, allowing coverage of the examination room from different angles to eliminate blind spots. Each camera feed is processed independently, and the results are aggregated to provide a holistic view of the examinee's activities. To maintain the system's performance, we employed continuous monitoring and periodic retraining strategies. The model's performance metrics, including precision, recall, and mean Average Precision (mAP), are regularly evaluated, and the model is updated with new data to adapt to emerging cheating techniques. The research paper is structured to provide a comprehensive overview of our project and its findings. It includes detailed sections on the system architecture, data collection and annotation processes, model training and evaluation, implementation of gaze detection, real-time alert generation, and performance analysis. Our results demonstrate the efficacy of the proposed system in enhancing the integrity and fairness of the examination process. (Soltane and Laouar, 20121), (Jadi, 2021)

2 PROPOSED METHODOLOGY

2.1 Methodology

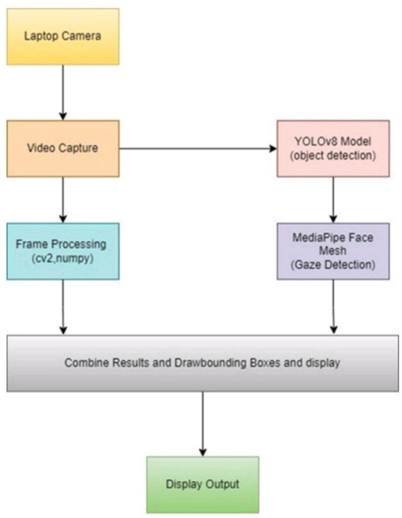

Figure 1: Proposed Methodology

The proposed framework for building a cheat detection model in online examinations involves a series of steps as seen in figure 1. It begins with data collection, where a comprehensive dataset of images capturing various cheating behaviors during simulated online exams is gathered. The collected data then undergoes preprocessing and splitting into training, validation, and testing subsets. Subsequently, the YOLOv8 (You Only Look Once, Version 8) object detection model is employed and trained on the prepared dataset to detect and classify cheating behaviors present in the images. The trained YOLOv8 model is then used to classify input images into "Cheating" or "No Cheating" categories based on the detected cheating behaviors. The performance of the trained model is evaluated using appropriate metrics, and the evaluation results can be used to refine and improve the model further through a feedback loop. The framework leverages computer vision techniques and the YOLOv8 model to automatically detect and classify cheating behaviors, thereby enhancing academic integrity and creating a fair assessment environment for online examinations.

2.2 Dataset Description

To develop and evaluate a robust cheat detection system for online examinations, a comprehensive dataset was manually collected. The dataset consists of images and annotations capturing various cheating behaviors exhibited by individuals during simulated examination scenarios. The complete dataset summary is shown in table 1.

Table 1: Dataset Summary

Description	**Details**
Participants (M/F)	30 (15/15)
Scenarios	Down, Left, Right, Mobile, Away, Earphone, Multiple
Environment	Controlled Exam
Purpose	Cheating Analysis

2.2.1 Data Collection

A total of 30 participants, comprising 15 males and 15 females, were recruited for the data collection process. These participants were instructed to simulate cheating behaviors in a controlled environment, mimicking real-world scenarios encountered during online examinations.

2.2.2 Cheating Scenarios

The participants were asked to engage in various cheating activities, including but not limited to:

- Using mobile phones: Participants were instructed to hold and interact with their mobile phones, simulating the act of accessing unauthorized information or communicating with others during the examination.
- Wearing headphones: Participants wore headphones, mimicking the behavior of receiving audio prompts or instructions from external sources.
- Utilizing smartwatches: Participants wore smartwatches, representing the potential use of such devices to access or receive information covertly.
- Looking away from the screen: Participants were instructed to frequently shift their gaze away from the simulated examination screen, indicating potential cheating by referring to external resources or seeking assistance from others.
- Exhibiting suspicious body language: Participants were encouraged to exhibit suspicious body language, such as fidgeting, nervous movements, or suspicious postures, which could potentially indicate cheating behavior.

2.2.3 Data Annotation

For each captured image, detailed annotations were provided, indicating the presence or absence of various cheating behaviors. These annotations included:

- Phone detected: Images where the participant was holding or interacting with a mobile phone were labeled as ”Phone detected.”
- Headphone detected: Images where the participant was wearing headphones were labeled as ”Headphone detected.”
- Smartwatch detected: Images where the participant was wearing a smartwatch were labeled as ”Smartwatch detected.”
- Looking away from the screen: Images where the participant's gaze was directed away from the simulated examination screen for an extended period were labeled as ”Looking away from the screen.”

The final dataset comprises approximately 1,200 annotated images, capturing a diverse range of cheating behaviors and scenarios. This dataset will serve as a valuable resource for training and evaluating machine learning models aimed at detecting cheating attempts during online examinations.

2.3 Equations

Gaze Estimation: The gaze scores lx_score, ly_score, rx_score, and ry_score for the left and right eyes are calculated using the landmark coordinates obtained from the MediaPipe FaceMesh model. These scores represent the relative position of the iris within the eye region.

Left Eye X Gaze Score:

$$lx_score = \frac{face_2d[468,0] - face_2d[130,0]}{face_2d[243,0] - face_2d[130,0]}, \tag{1}$$

Left Eye Y Gaze Score:

$$ly_score = \frac{face_2d[468,1] - face_2d[27,1]}{face_2d[23,1] - face_2d[27,1]}, \tag{2}$$

Right Eye X Gaze Score:

$$rx_score = \frac{face_2d[473,0] - face_2d[463,0]}{face_2d[359,0] - face_2d[463,0]}, \tag{3}$$

Right Eye Y Gaze Score:

$$ry_score = \frac{face_2d[473,1] - face_2d[257,1]}{face_2d[253,1] - face_2d[257,1]}, \tag{4}$$

where $face_2d$ is an array containing the 2D facial landmark coordinates.

Gaze Direction: The gaze direction is determined based on the gaze scores using the following conditions:

$$direction = \begin{cases} \text{Looking Right,} & \text{if } lx_score > 0.6 \text{ or } rx_score > 0.6 \\ \text{Looking Left,} & \text{if } lx_score < 0.4 \text{ or } rx_score < 0.4 \\ \text{Looking Up,} & \text{if } ly_score > 0.6 \text{ or } ry_score > 0.6 \\ \text{Looking Down,} & \text{if } ly_score < 0.4 \text{ or } ry_score < 0.4 \\ \text{Looking Straight,} & \text{otherwise} \end{cases} \tag{5}$$

The provided equations are used to estimate gaze direction from facial landmark coordinates obtained from the MediaPipe FaceMesh model. Equations (1) and (2) calculate the horizontal and vertical gaze scores for the left eye, respectively, by taking the relative position of the iris landmark with respect to the eye's corner and top/bottom landmarks. Equations (3) and (4) perform similar calculations for the right eye. Equation (5) then determines the overall gaze direction (Looking Right, Left, Up, Down, or Straight) based on these gaze scores, using predefined thresholds. This gaze estimation technique allows for real-time tracking of eye movements and gaze direction, which can be useful in various applications such as human-computer interaction, attention monitoring, and behavioral analysis. Head Pose Direction: The head pose direction is determined based on the adjusted rotation vectors using the following conditions:

$$head\_direction = \begin{cases} \text{Facing Right :} \\ \text{if} l\_gaze\_rvec[2][0] > 0 \\ \text{Facing Left :} \\ \text{if} l\_gaze\_rvec[2][0] < 0 \\ \text{Facing Forward :} \\ \text{otherwise} \end{cases} \quad (6)$$

The head pose direction is determined from the adjusted rotation vectors of the left and right eye landmarks. If the x-component of either eye's rotation vector is positive, the head is classified as "Facing Right". If the x-component is negative for either eye, the head is classified as "Facing Left". In all other cases, where the x-components are zero for both eyes, the head pose is classified as "Facing Forward". This approach utilizes the rotation information extracted from facial landmarks to estimate the overall head orientation.

3 RESULTS

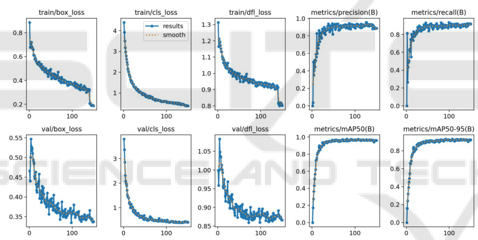

Figure 2: YOLOv8 training results

The figure 2., presents a comprehensive overview of a YOLOv8 object detection model's training progress. It showcases various training and validation loss metrics (box, class, and dfl losses) which consistently decrease over time, indicating effective learning. Simultaneously, performance metrics such as precision, recall, and mean Average Precision (mAP) demonstrate steady improvement, eventually stabilizing at high values. This overall trend across multiple metrics suggests that the model is learning successfully, generalizing well to validation data, and achieving strong object detection performance as the training progresses through its epochs.

The provided figure 3., illustrates a cheat detection system in an online examination, effectively identifying the examinee's face and gaze direction, along with detecting the presence of a mobile phone. The system indicates the examinee is looking down at the device, suggesting potential cheating behavior.

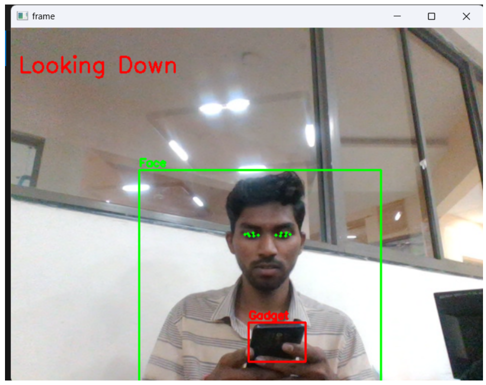

Figure 3: Mobile Detected

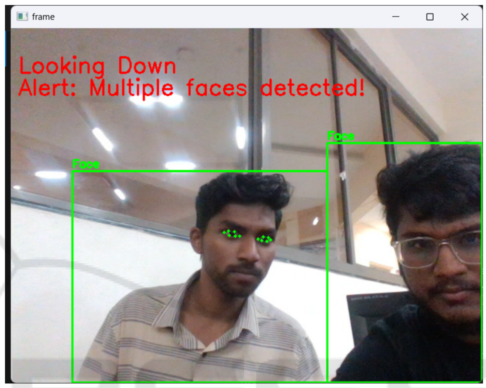

Figure 4: Multiple Persons Detected

The provided figure 4.,illustrates a cheat detection system in an online examination, identifying the presence of multiple faces within the frame. The system highlights the primary examinee looking down and raises an alert for multiple detected faces, indicating potential collusion or assistance.

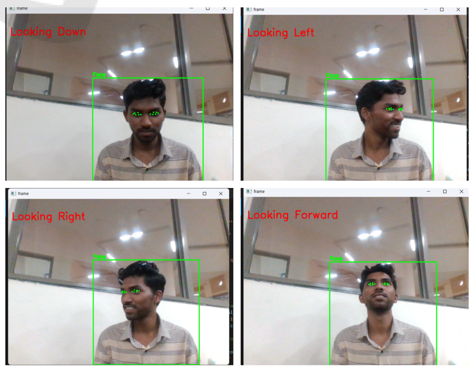

Figure 5: Gaze Direction

The provided figure 5.,demonstrates a cheat detection system that tracks and labels an examinee's gaze direction in various orientations: looking down, left, right, and forward. The system's accurate gaze detection, indicated by green dots on the eyes and corresponding labels, allows for comprehensive monitoring of the examinee's attention during an online examination. This capability is essential for identifying suspicious behavior, ensuring the integrity of the examination process.

Table 2: YOLOv8 Object Detection Model Results

Metric	Value
Precision	0.9920
Recall	0.9987
mAP50	0.9950
mAP50-95	0.9348

Model Performance Evaluation and Updation

- Evaluation Metrics: The model's performance was assessed using the metrics as seen in table 2.
- Evaluation Process: The evaluation was conducted on a validation dataset comprising various annotated images with various exam cheating scenarios. The confusion matrix was used to calculate precision and recall, while mAP was calculated following the standard COCO evaluation method.
- Model Updating:
  - Data Collection: New data was collected from recent exams, focusing on emerging cheating techniques.
  - Data Annotation: The new dataset was annotated with labels for cheating-related objects and activities.
  - Model Retraining: The YOLOv8 model was retrained using the combined original and new datasets.
- Documentation and Reporting: Each evaluation and retraining cycle is meticulously documented. Reports include performance metrics, changes in model architecture, and qualitative assessments of the model's detection capabilities.

4 CONCLUSIONS

Our cheat detection system leveraging the YOLOv8 model demonstrated remarkable accuracy in identifying multiple persons, unauthorized gadgets, and suspicious gaze directions. This system significantly enhances the integrity of online examinations by providing real-time alerts, thereby reducing the chances of cheating. The solution's versatility allows its application across educational institutions, certification bodies, and other scenarios requiring stringent monitoring and compliance. Furthermore, the potential for adaptation to secure remote work environments and online interviews showcases the broad applicability of AI-driven solutions. This project underscores the critical role of advanced object detection models in maintaining fairness and credibility in various online activities. The integration of deep learning models like YOLOv8 is crucial for integrity detection during online examinations, ensuring a fair and secure assessment environment. Continuous innovation in cheat detection methodologies is essential to keep up with evolving challenges and maintain the trust and reliability of online platforms.

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