Integrated 3-Layer Online Test Cheating Detection System using YOLO8, InsightFace, and GazeTracking Modules

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Abstract: The adoption of online test has introduced significant challenges in maintaining academic integrity, particularly in detecting cheating behaviors in real time. This research proposes an intelligent proctoring system that integrates image processing and computer vision techniques to automatically detect suspicious participant behavior during online test. The system integrates a YOLOv8s model based on YOLO neural network algorithm to localize and classify facial states and suspicious objects in each video frame. This detection layer is complemented by an InsightFace as face recognition module, which extracts deep facial embedding features and performs similarity matching against a registered reference image to continuously verify participant identity and detect impersonation attempts. In parallel, a GazeTracking module analyzes eye landmarks and pupil dynamics to monitor eye behavior, including blinking and significant gaze deviation, providing additional behavioral cues related to attention and potential cheating. Together, these components form a synchronized computer vision module that performs real-time analysis from live video streams, allowing the system to classify behavioural states such as abnormal head orientation, multiple faces, foreign objects, no face detected, identity mismatch, and eye closure. The YOLOv8s model was trained on a self-collected dataset of 1,320 curated images from a single participant across four behavioral classes and four controlled lighting conditions, achieving a precision of 0.9856, recall of 0.9903, mAP@50 of 0.9918, and mAP@50-95 of 0.9656 at training epoch 168 on the held-out validation set. The findings demonstrate that deep learning based visual monitoring can effectively support automated online exam supervision, offering a scalable and reliable proctoring systems.

Keywords: Online test, Cheating detection, YOLO, InsightFace, GazeTracking.

Introduction

The development of digital technology has brought about major changes in various areas of life, including the education sector (Gusniwati & Rahmawati, 2024). The learning process, which originally took place face to face, is now increasingly shifting to an online learning model. One important element of online learning is the implementation of online examinations, which allow students to take academic assessments without having to be physically present in an examination room.

However, behind this convenience, new challenges arise in terms of academic integrity and honesty. Online examination systems that are not directly supervised could open great opportunities for various forms of cheating. Examinees may engage in actions such as collaborating with others (collusion), using additional devices (mobile phones, dual screens, or communication applications), or manipulating their identity by using a proxy or facial manipulation technology such as *deepfake* (Hasibuan & Hendrik, 2025). According to various recent studies, academic cheating in online examination systems has increased significantly since 2020 and has become one of the main issues in the implementation of e-learning in various educational institutions.

In online examinations, supervision of participants is generally carried out in simple ways, such as using a webcam or screen recording (S. Purwanto et al., 2022). However, this system still has fundamental weaknesses such as supervisors still have to monitor manually, while the human ability to supervise many participants simultaneously is limited. Therefore, an AI based automated proctoring system is needed that is capable of real-time supervision and detecting indications of cheating without direct intervention.

Advances in computer vision and deep learning technology have opened enormous opportunities to address this issue. One rapidly developing method is face and object detection, which is the ability of a system to automatically recognise and track specific objects from images or videos (Abdurrasyid et al., 2022). The previous model such as *You Only Look Once* (YOLO) version 8s, particularly YOLOv8s can identify various objects within a single image frame, including faces, hands, and devices such as mobile phones. With these advantages, YOLOv8s has the potential to become the primary model in visual based fraud detection systems (Putu Ary Sri Tjahyanti et al., 2024).

However, these studies are generally still limited to only one aspect of behaviour, such as object detection without facial expression analysis or without participant identity recognition. There are just a few integrated system that combines face and object detection, identity face recognition, and eye movement analysis (head, object, face and eye analysis) to detect various forms of cheating during online examinations (Jatnika et al., 2023). Furthermore, the application of the YOLOv8s model in the context of online examinations is still very rare, even though this model offers significant improvements over its predecessors in terms of accuracy and detection speed (Nur Aziz Thohari et al., 2025). Another important challenge is how the system can maintain privacy and ethical use of facial data, so that the technology developed does not violate the rights of exam participants (S. Purwanto et al., 2022).

This system is designed to detect several forms of cheating behaviour, such as looking away for too long, using additional devices such as mobile phones, and potential cheating detected from facial identity mismatches (Purwanto & Putra, 2025). The detection process will be carried out through a combination of identity verification (*face recognition*), and analysis of gaze direction and facial movements (*motion detection*) (Potluri et al., 2023).

This research is expected to produce a prototype of an intelligent proctoring system (S. Purwanto et al., 2022) that is not only capable of detecting cheating behaviour accurately and efficiently, but also makes a real contribution to improving academic integrity in the digital age. In addition, the results of this research are also expected to serve as an initial reference in the development of a deep learning based monitoring system that is ethical, transparent, and adaptive, in accordance with the principles of academic honesty and personal data protection (Jatnika et al., 2025).

Research Method

In this research, the system developed is an artificial intelligence based online exam proctoring system that utilises computer vision technology to detect potential cheating by real-time analyze of participant webcam. The main focus of the research is not only on theoretical analysis, but also on the actual implementation of the system, performance testing, and evaluation of the results obtained from the system.

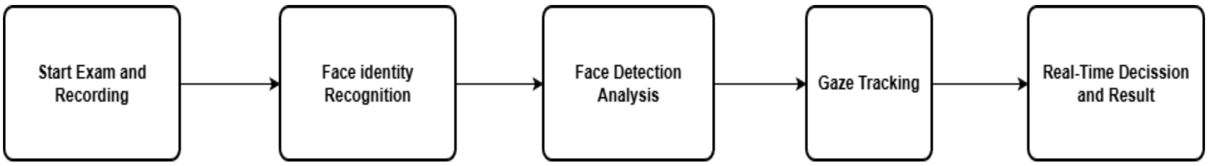

Figure 1. Integrated system pipeline

This research proposes a computer vision based proctoring framework that detects cheating behavior during online examinations by combining deep learning-based object detection with facial verification and gaze analysis. The research methodology used was the Experimental Design that consists of five main stages: dataset preparation and annotation, Automatically Dataset Labeling, YOLOv8s model training, evaluation model, and real-time system integration (Drantantiyas et al., 2023).

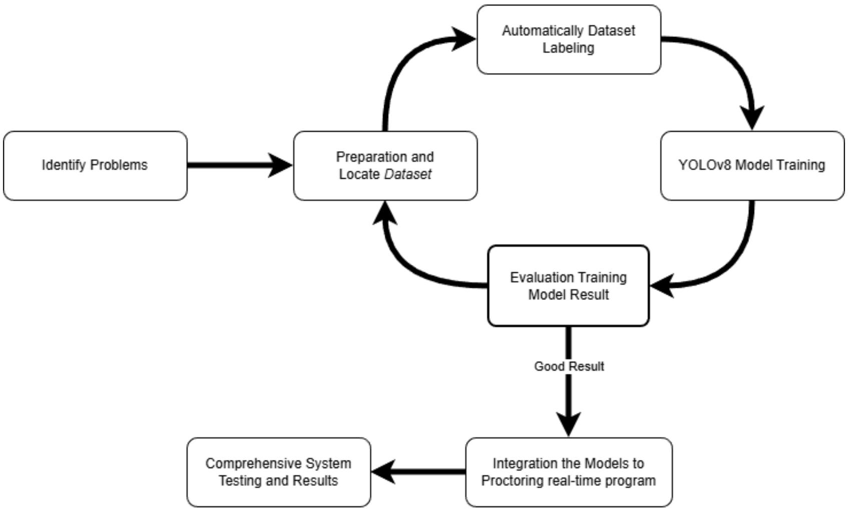

Figure 2. Experimen design flow

2.1. Dataset preparation and labeling

2.1.1. Dataset source

The dataset used in this study was captured from a self collected image dataset under controlled experimental conditions. All images were obtained from simulated online examination sessions, where a Pilot/Proof-of-Concept performed predefined behaviors representing normal and cheating scenarios.

To improve robustness, each class was recorded under four lighting categories as following; light_A (bright), B (normal), C (dim), and D (dark). These categories ensuring diversity in brightness and contrast conditions (Juliandy et al., 2024).

The dataset represents variations in participant behavior, lighting conditions, and environmental disturbances that may occur during online examinations (Essahraui et al., 2025). Each image was stored in PNG format and manually organized according to behavioral categories relevant to cheating detection.

Before automatic annotation, the dataset consisted of manually captured images grouped by behavioral class and lighting condition. The initial distribution of images is summarized in Table below.

Table 1. Dataset distribution by class and lighting condition

Class	light_A	light_B	light_C	light_D	Total Images
face_normal	71	58	146	139	414
face_not_forward	89	106	41	165	401
foreign_object	255	153	302	186	896
multi_face	42	42	71	85	240

The dataset therefore contained 1,951 images in total. The lighting categories do not represent separate datasets but rather environmental variations within each class (Islam, 2023). This design ensures that the model learns robust visual representations under heterogeneous illumination conditions.

Eye movement and face identity verification were not included as dataset classes of YOLOv8s model because such tasks are not optimally handled by object detection models (Gündüz & Işık, 2023). Instead, these features were implemented separately using specialized libraries: InsightFace for face recognition and GazeTracking for eye behavior analysis.

2.1.2. Automatic labelling

Manual labelling of large amont image datasets is time consuming and prone to inconsistency. Therefore, an automated labelling method was implemented using a hybrid approach that combining face detection and object detection models.

The method utilizes the InsightFace framework for facial detection and pose estimation (Potluri et al., 2023). Only images satisfying strict filtering criteria were retained, including minimum face size, frontal pose constraints, and confidence thresholds adjusted for each lighting condition. Contrast Limited Adaptive Histogram Equalization (CLAHE) was applied as a preprocessing step to normalize illumination for image that effected by brightness and contrasts (Okyere-Gyamfi et al., 2025).

$$I' = \mathrm{CLAHE}(I) \tag{1}$$

Variable description

- I: original input image (raw image) from the webcam
- I': image of contrast enhancement after CLAHE
- $\mathrm{CLAHE}(\cdot)$: function of Contrast Limited Adaptive Histogram Equalization

CLAHE enhances the local contrast of the image to make facial features clearer. This is important so that the face detection model works stably in different lighting conditions. Valid samples were then automatically converted into bounding box format and stored as paired image label files (Potluri et al., 2023).

This method will transform image captures into a structured training dataset with minimal human intervention:

$$x_c = \frac{x_1 + x_2}{2W} \tag{2}$$

$$y_c = \frac{y_1 + y_2}{2H} \tag{3}$$

$$w = \frac{x_2 - x_1}{W} \tag{4}$$

$$h = \frac{y_2 - y_1}{H} \tag{5}$$

Variable description

- x_1, y_1 : coordinates of the top left corner of the bounding box (pixel)
- x_2, y_2 : bottom right corner coordinates of the bounding box (pixels)
- W: image width (pixels)
- H : image height (pixels)
- x_c : centre coordinates of the bounding box on the x-axis (normalised 0–1)
- y_c : centre coordinates of the bounding box on the y-axis (normalised 0–1)
- w : relative bounding box width relative to the image
- h : bounding box height relative to the image

2.1.3. Dataset Splitting

After labelling, all images were consolidated into a unified dataset and automatically split into training and validation datasets specifically optimized for supervised training (Septiandi et al., 2021).

Table 2. Dataset class distribution

Class	Description	Total Images	Training	Validation
face_normal	Participant facing forward in a normal posture.	410	328	82
face_not_forward	Participant looking away or turning sideways.	385	311	74
multi_face	More than one face visible in the frame.	202	154	48
foreign_object	Presence of unauthorized objects (e.g., smartphone).	323	263	60

Not all dataset images were directly suitable for training. Some images contained occlusions, ambiguous poses, insufficient face visibility, or detection failures. Therefore, a automated labelling was applied to filter and refine the dataset.

Only images that satisfied all validation criteria face detectability, pose constraints, size thresholds, and absence of unintended objects were retained. As a result, the curated dataset contains fewer samples than the raw acquisition set. This reduction is not a limitation but rather a deliberate quality control step designed to eliminate ambiguous or noisy samples that could negatively affect model learning. Randomised shuffling with a fixed seed ensures reproducibility. This stage represents the transition from image capture to a structured learning dataset.

The filtering process improves dataset consistency by ensuring that each retained image clearly represents its intended behavioral class (Khoiriyah et al., 2025). In supervised deep learning, label purity and visual clarity are often more critical than dataset size alone. By prioritizing high-confidence samples, the automatic labelling enhances training stability and reduces the risk of model confusion caused by mislabeled or low quality data. The curated dataset therefore provides a cleaner representation of behavioral patterns relevant to online exam monitoring, which directly contributes to the high detection performance observed during training.

2.2. YOLOv8s Model Training

The face and object detection analysis is based on YOLOv8s model, a single stage detector known for its balance between accuracy and real-time performance (Ajayi et al., 2024). A pretrained YOLOv8s model was selected as the base architecture and fine-tuned on the dataset. The optimization objective minimizes a composite loss:

$$L = L_{box} + L_{obj} + L_{cls} \tag{6}$$

Variable description:

- L: minimised total loss during training
- L_{box}: bounding box regression loss (object position error)
- L_{obj}: loss of objecthood (belief in the existence of objects)
- L_{cls}: loss classification of object classes

Transfer learning was applied to accelerate convergence and leverage pretrained feature representations and performed using GPU acceleration with mixed precision inference to maximize hardware utilization (Kljucaric & George, 2023). As for that YOLOv8s model, the training configuration need to be adjust for the maximum result as following config:

Table 3. YOLOv8 training configuration

Parameter	Value
Input (dataset) resolution	640 × 640
Epochs	200
Data caching	Disk
Model	yolov8s.pt

2.3. Model Evaluation

Model performance was evaluated on the validation dataset using standard object detection metrics, including precision, recall, F1 score, and mean Average Precision (mAP). Confusion matrices were generated to analyze class wise prediction behavior (Drantantiyas et al., 2023). Model performance is evaluated using precision, recall, and F1 score (Putra & Mulyana, 2024):

$$Precision = \frac{TP}{TP+FP} \tag{7}$$

$$Recall = \frac{TP}{TP+FN} \tag{8}$$

$$F1 = 2 \times \frac{Precision \cdot Recall}{Precision+Recall} \tag{9}$$

Variable description

- TP (True Positive): correct detection of existing objects
- FP (False Positive): incorrect detection of objects that do not exist
- FN (False Negative): objects that fail to be detected
- Precision: accuracy of detection
- Recall: detection completeness
- F1: average harmonic precision and recall

Recall measures the proportion of correctly detected objects among all ground truth objects. High recall implies that the model successfully captures most target objects without overlooking important instances. Training curves and evaluation statistics were automatically recorded for further analysis.

2.4. Face Recognition Module

To enhance system security, a face recognition module is incorporated to verify participant identity. The module uses deep facial embeddings generated by a pretrained neural network model (S. Purwanto et al., 2022).

During real-time operation, detected faces are compared with the reference embedding using cosine similarity (Terampe & Arif Pramudwiatmoko, 2025):

$$Similarity = \frac{a \cdot b}{\|a\|\|b\|} \tag{10}$$

Variable description

- a: reference face embedding vector
- b: facial embedding vector from real-time frames
- $\| a \|$: norm (length) of vector a

- $\parallel b \parallel$: norma vector b
- Similarity: cosine similarity value (range -1 to 1)

Beyond object detection, the system incorporates face recognition and gaze analysis to enhance monitoring reliability. Face identity verification relies on cosine similarity between facial embeddings:

$$face\ match = \text{Cosine Similarity value} \geq \text{Threshold} \tag{11}$$

Where Threshold is the minimum similarity value for determining identity matching. If the similarity score falls below a threshold value, a face mismatch violation is triggered. This mechanism ensures identity consistency throughout the examination session.

2.5. Gaze Tracking Module

The gaze tracking component analyzes eye direction and blinking behavior to detect signs of distraction or inattentiveness. The module processes eye regions to estimate gaze direction and blinking events (Liu et al., 2024). Blink detection is particularly important for identifying prolonged eye closure, which may indicate fatigue or disengagement. The module classifies gaze into three states: neutral (looking straight), looking away, and blinking.

This behavioral analysis complements object detection by capturing subtle attention related cues that cannot be inferred from bounding boxes alone (Murjitama et al., 2025). Detection of prolonged eye deviation or abnormal blinking patterns may indicate inattentiveness or suspicious activity. While gaze estimation accuracy can be affected by webcam resolution and lighting conditions, its integration adds an important behavioral to the proctoring system.

2.6. Real Time Proctoring System Integration

The trained of YOLOv8 model was integrated into a real-time proctoring application that processes live webcam streams. The system combines three modules:

1) YOLO based behavior detection
2) Facial identity verification using InsightFace embeddings
3) Gaze tracking for eye movement analysis

These modules operate asynchronously using interval based inference scheduling to maintain high frame rates. Each incoming video frame undergoes selective analysis based on predefined intervals. Heavy computations such as object detection and facial recognition are executed periodically, while cached results are reused between intervals to reduce latency.

Several optimization strategies were implemented to ensure stable high speed processing and enable smooth real-time visualization while maintaining detection reliability:

- GPU accelerated inference
- Mixed precision computation
- Frame caching and asynchronous rendering
- Reduced buffer latency
- Selective frame analysis

Result and Discussion

Every method of experiments has been conducted in this research, the outcomes obtained provide a foundation for evaluating the effectiveness of the proposed integrated system. The training process, model optimization, and subsequent evaluations have yielded results that reflect both the strengths and limitations of the chosen methodology.

Presenting these findings is essential not only to demonstrate the technical performance of the model but also to interpret their significance in relation to the research objectives. The results are examined, supported by quantitative metrics, to provide a comprehensive understanding of how the integrated system performed and what insights can be drawn from its behavior. This research offering critical reflections for other researchers to do the same research.

3.1. Training Model Performance

The YOLOv8 model was trained for 200 epochs using all train dataset designed to detect cheating related behaviors. The training process demonstrates stable convergence across all loss components, as illustrated results figure in below. The curves show a consistent decrease in box loss, classification loss, and distribution focal loss (DFL), accompanied by a steady increase in evaluation metrics.

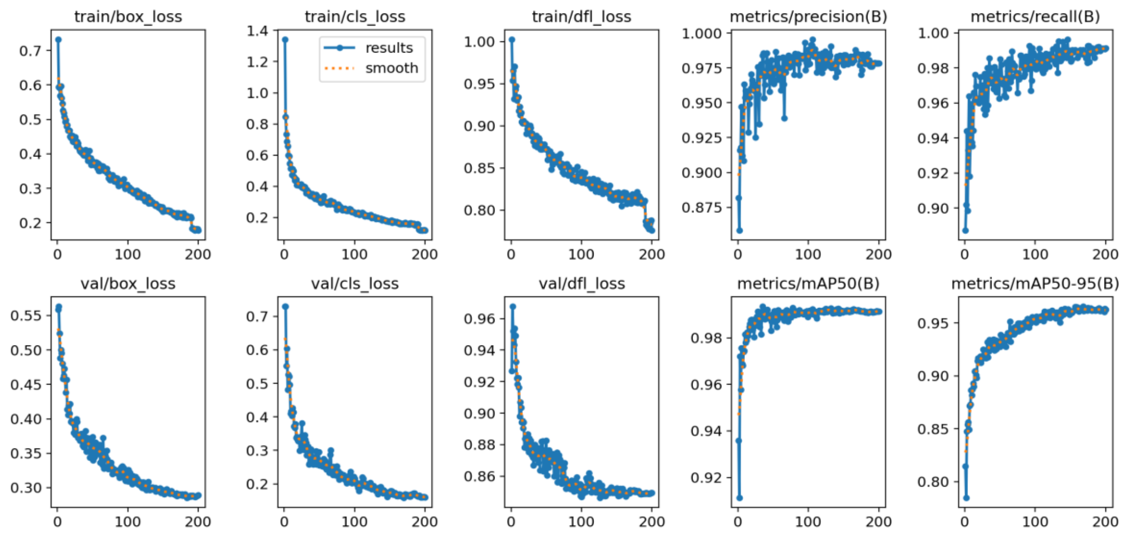

Figure 3. results.png as Training curves of YOLOv8

A steady decrease in loss throughout the epoch indicates that the model successfully learned the patterns of the dataset without any signs of overfitting.

In the final epoch, the loss curve tends to flatten, indicating that the model has reached convergence. This convergence indicates that the optimisation process has reached a stable condition, where additional training no longer provides significant improvements to the error. The overall detection performance is summarized by the mean Average Precision (mAP):

$$mAP = \frac{1}{N}\sum_{i=1}^{N} A\,P_i \tag{12}$$

Variable description

- L: minimised total loss during training
- L_{box}: bounding box regression loss (object position error)
- L_{obj}: loss of objecthood (belief in the existence of objects)

The mAP is then computed as the arithmetic mean of AP values across all classes, representing the overall detection quality of the model. A higher mAP indicates that the detector achieves both strong accuracy and consistency across multiple behavioral classes. Where N is the number of classes and $AP_i$is the average precision for class i. The best performing epoch was recorded at epoch 168. The quantitative performance is summarized in Table below.

Table 4. Best training performance metrics

Metric	Value
Precision	0.9856
Recall	0.9903
mAP@50	0.9918
mAP@50–95	0.9656

The small gap between mAP@50 and mAP@50–95 suggests that the model maintains high localization accuracy even under stricter intersection over union (IoU) thresholds. The alignment between training and validation curves further indicates that overfitting is minimal and that the model generalizes well to unseen samples.

3.2. Visual Model Evaluation

The Model performance is evaluated using standard object detection metrics. Precision measures the proportion of correct detections among all detections. A high precision value indicates that most detections produced by the model are accurate and that the system rarely generates false alarms.

The outputs generated during validation including labeled samples, predicted samples, and confusion matrices provide clear evidence of the model's reliability.

Figure 4. Validation Samples with Ground Truth Labels (val_batch0_labels)

This is one of three visualization validation samples with annotated labels demonstrates that the dataset was well-prepared and representative. The bounding boxes and class labels are clearly defined, providing a reliable reference for evaluating prediction quality.

Figure 5. Validation Samples with Model Predictions (val_batch0_pred)

The corresponding predictions on the same three samples show a strong alignment with the ground truth. The bounding boxes are accurately localized, and class assignments are consistent, indicating that the YOLOv8s model successfully learned the object features during training.

Class level performance is analyzed using the confusion matrices shown in confusion matrix figure below.

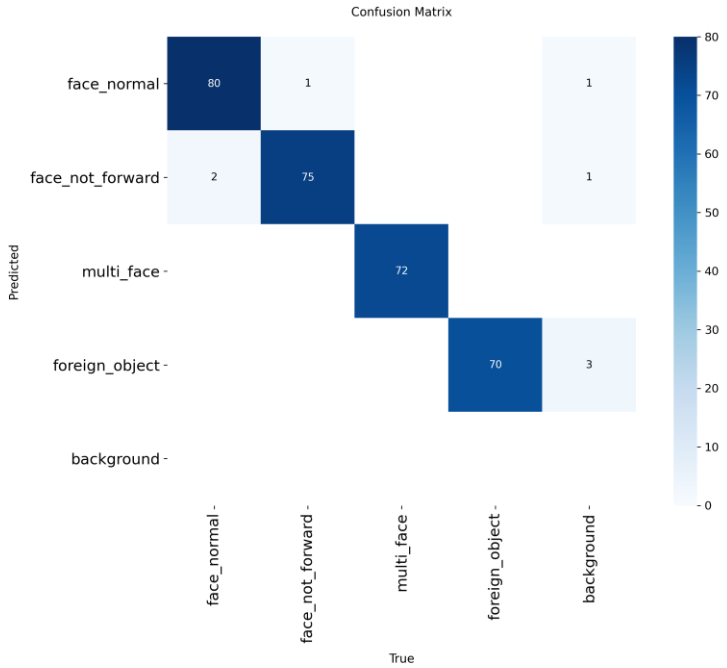

Figure 6. Confusion_matrix.png as Confusion matrix

Minor confusion is observed between *face_normal* and *face_not_forward*, which is understandable because subtle head orientation differences can be difficult to distinguish under varying lighting and camera angles.

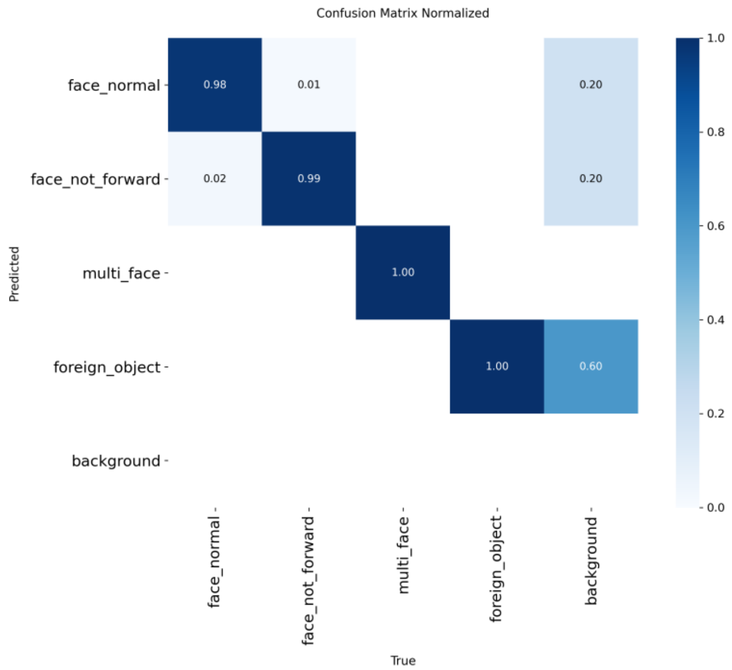

Figure 7. Confusion_matrix_normalized.png as Normalized confusion matrix

Similarly, occasional confusion between *multi_face* and *foreign_object* may arise when additional objects partially resemble facial features or when occlusion occurs. Despite these challenges, the normalized confusion matrix demonstrates that misclassification rates remain low across all classes.

This balanced class level performance confirms that the trained model can reliably distinguish different cheating related behaviors, which is critical for real-world proctoring applications.

3.3. Face Recognition Performance

During system operation, a facial embedding vector is extracted from each detected face and compared with the stored reference embedding using cosine similarity. The similarity score determines whether the detected face matches the registered participant. A predefined threshold is used to classify identity consistency.

When the participant's face is clearly visible and oriented toward the camera, similarity scores consistently exceed the matching threshold, resulting in stable identity verification. Conversely, when a different person appears or when the face is partially occluded, the similarity score decreases significantly, triggering a mismatch warning.

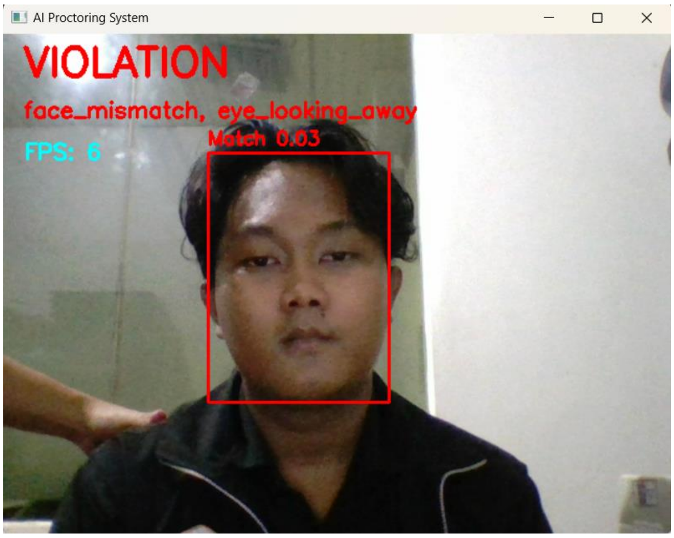

Figure 8. Face mismatch detection of warning indication

This behavior confirms that the embedding-based verification method effectively distinguishes between authorized and unauthorized participants. The system demonstrates robustness against minor variations in facial expression and illumination, which is critical for practical online examination environments.

The integration of face recognition with object detection strengthens the reliability of the proctoring system by ensuring that behavioral analysis is consistently associated with the correct participant identity.

3.4. Gaze Tracking and Eye Behavior Analysis

Blinking detection is particularly stable identifies closed-eye states, which may indicate drowsiness or intentional eye closure during the examination.

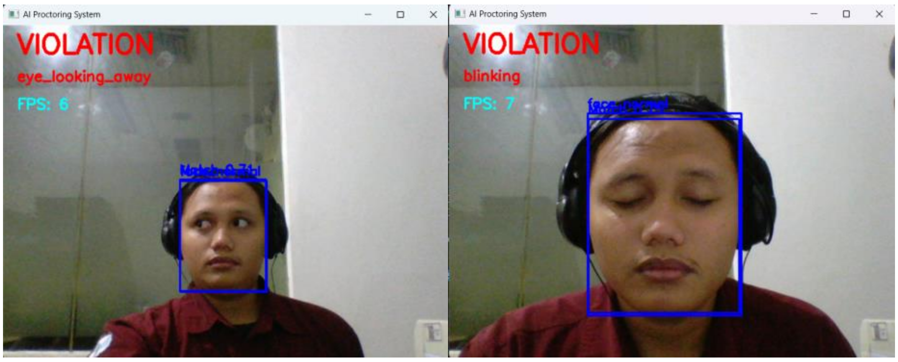

Figure 9. Detection of Eye looking away and blinking behavior during real-time monitoring

However, fine-grained gaze direction detection is more sensitive to lighting conditions and camera quality. While large eye movements are reliably captured, subtle gaze shifts may not always be detected with the same consistency. Despite this limitation, module provides valuable supplementary behavioral with object detection.

3.5. Real Time Proctoring System Integration

The trained YOLOv8s model is integrated into a real-time proctoring program that combines face recognition, and gaze tracking. The system processes webcam input and evaluates behavioral compliance in real time.

The final system aggregates signals from all modules to determine a global status of either 'NORMAL' or 'VIOLATION'. This fusion improves robustness by combining complementary sources of information. Instead of relying solely on object detection and also recognition, the system evaluates identity verification object detection and attention pattern simultaneously, resulting in more comprehensive proctor solution.

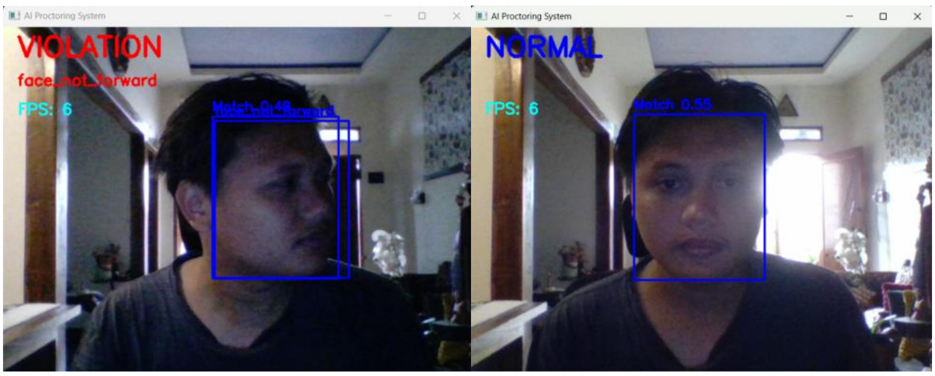

Figure 10. Capture of violation and normal behavior status

This design ensures that the system remains responsive without sacrificing detection accuracy.

By synchronizing these three distinct layers, this research addresses the limitations of unimodal systems and provides a more comprehensive framework for maintaining integrity in remote testing environments.

Conclusions

This research presents an intelligent online exam proctoring system that integrates YOLOv8s model for face and object detection, with InsightFace for face recognition and gaze tracking to detect cheating related behaviors. The system is capable of identifying multiple violation categories, including abnormal head orientation, multiple faces, foreign objects, identity mismatch, and abnormal eye behavior, forming a comprehensive monitoring framework.

Experimental results show that the trained YOLOv8 model achieves performance peak in epoch 168 with precision of 0.9856, recall of 0.9903, and mAP@50 of 0.9918. Confusion matrix analysis indicates minimal inter class misclassification, demonstrating strong discriminative capability across different behavioral classes and lighting conditions.

The integration of the trained model into a real-time proctoring system shows that the system operates stably at high accuracy and precision. Although the GPU utilization remains moderate, the interval based inference strategy allows efficient balancing between computational cost and detection responsiveness. The combination of YOLO algorithm detection, face embedding similarity matching, and gaze tracking forms a verification pipeline that increases system robustness compared to single modality approaches.

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