

AutoOEP - A Multi-modal Framework for Online Exam Proctoring

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Abstract

The burgeoning of online education has created an urgent need for robust and scalable systems to ensure academic integrity during remote examinations. Traditional human proctoring is often not feasible at scale, while existing automated solutions can be intrusive or fail to detect a wide range of cheating behaviors. This paper introduces AutoOEP (Automated Online Exam Proctoring), a comprehensive, multi-modal framework that leverages computer vision and machine learning to provide effective, automated proctoring. The system utilizes a dual-camera setup to capture both a frontal view of the examinee and a side view of the workspace, minimizing blind spots. Our approach integrates several parallel analyses: the *Face Module* performs continuous identity verification using ArcFace, along with head pose estimation, gaze tracking, and mouth movement analysis to detect suspicious cues. Concurrently, the *Hand Module* employs a fine-tuned YOLOv11 model for detecting prohibited items (e.g., mobile phones, notes) and tracks hand proximity to these objects. Features from these modules are aggregated and fed into a Long Short-Term Memory (LSTM) network that analyzes temporal patterns to calculate a real-time cheating probability score. We evaluate AutoOEP on a custom-collected dataset simulating diverse exam conditions. Our system achieves an accuracy of **90.7%** in classifying suspicious activities. The object detection component obtains a mean Average Precision (mAP@.5) of **0.57** for prohibited items, and the entire framework processes video streams at approximately 2.4 frames per second without a GPU. The results demonstrate that AutoOEP is an effective and resource-efficient solution for automated proctoring, significantly reducing the need for human intervention and enhancing the integrity of online assessments.

Introduction

The rapid expansion of online education has made ensuring academic integrity in remote assessments a paramount challenge for institutions. Preventing cheating during online hiring tests or interviews for companies is also incomplete without incorporating multiple modalities or variables to flag cheating. While traditional proctoring is not scalable,

various automated solutions have emerged. Early systems focused narrowly on identity verification to prevent impersonation, using face recognition to confirm the test-taker's presence (Idemedia et al. 2016; Garg et al. 2020). However, these systems do not address the broader spectrum of in-exam misconduct.

To capture more nuanced behaviors, researchers developed multi-modal frameworks that analyze multiple cues simultaneously, such as gaze direction, head pose, and system activity (Atoum et al. 2017; Prathish, Narayanan, and Bijlani 2016). While more comprehensive, these approaches exhibit significant limitations. Some rely on specialized hardware like wearable cameras, hindering widespread adoption (Atoum et al. 2017), while others fail to detect the use of prohibited physical items like mobile phones or notes (Tejaswi, Venkatramaphanikumar, and Venkata Krishna Kishore 2023). More recent systems incorporate object detection (Verma et al. 2023), yet they typically only flag the presence of an illicit item, struggling to differentiate it from active use. This lack of contextual understanding, coupled with a reliance on single-frame analysis, often leads to a high rate of false positives and fails to capture cheating behaviors that unfold over time.

To address the aforementioned shortcomings, this paper introduces AutoOEP, a comprehensive, multi-modal automated proctoring framework designed for high accuracy and practical deployment, with the following features:

- Dual-camera framework with standard webcams to simultaneously capture a frontal view of the examinee and a side view of their workspace, thereby minimizing blind spots.
- A Face Module performs continuous identity verification and tracks facial cues.
- A unique hand-object interaction module that moves beyond simple presence detection by calculating the proximity between a user's hands and prohibited items, which provides a more accurate assessment of active cheating.
- Application of a temporal LSTM-based model to analyze sequences of these behavioral features to generate a cheating probability score, enabling the system to understand context and reduce the false positives common in frame-by-frame analysis.
- Validation of the system through a comprehensive eval-

uation on a custom-collected dataset, demonstrating its effectiveness and real-time performance.

In the next section, we review related work in automated proctoring followed by the methodology of the system. Then we present our experimental results and finally the concluding remarks.

Literature Review

Online exam proctoring has become increasingly important in recent years, especially with the rapid growth of distance learning and remote education. Early and foundational work in this domain primarily focused on verifying the test-taker's identity. For instance, several studies proposed lightweight solutions centered on face recognition to prevent impersonation. Approaches by (Idemudia et al. 2016) and (Garg et al. 2020) utilized facial recognition at the beginning of and intermittently during the exam to confirm the candidate's identity. Similarly, (Sun 2023) proposed a system using classical computer vision techniques for face matching to automate identity checks. While crucial for preventing proxy test-takers, these systems are limited as they do not address the wide array of cheating behaviors that can occur during an exam. Other single-modality systems, such as the work by (Dilini et al. 2021), focused exclusively on eye-gaze tracking to detect when a student looks away from the screen, demonstrating the limitations of a narrow analytical focus.

Multi-Modal Proctoring Frameworks

Recognizing the multifaceted nature of cheating, researchers have increasingly adopted multi-modal approaches that integrate several data streams. A pioneering study by (Atoum et al. 2017) introduced a comprehensive system using both a standard webcam and a wearable camera. Their method analyzed face identity, gaze, speech, text from notes, and active computer windows, feeding these features into an SVM classifier. Although robust, this approach relied on specialized hardware (a wearcam) and lacked temporal analysis.

Subsequent research has aimed to achieve multi-modal analysis using standard hardware. Systems like ProctorNet by (Tejaswi, Venkatramanikumar, and Venkata Krishna Kishore 2023) and ProctorEx by (Kasinathan et al. 2022) combine facial cues analysis, including head pose estimation, gaze tracking, and mouth movement, to infer suspicious behavior. For example, (Prathish, Narayanan, and Bi-jlani 2016) developed a system analyzing face landmarks, head pose, and system usage to flag anomalies like face disappearance or multiple faces. However, a significant limitation of these systems is the absence of prohibited object detection, leaving a major cheating vector unmonitored.

Object Detection and Interaction Analysis

More recent studies have incorporated object detection to identify illicit items in the test-taker's environment. (Ozgen et al. 2021) developed a pipeline using a MobileNet-SSD model to detect mobile phones and additional people in the frame. Likewise, (Verma et al. 2023) proposed a comprehensive system using YOLOv3 (Redmon and Farhadi 2018) to

detect objects like cell phones and books, alongside modules for emotion detection and face spoofing.

While these systems can detect the presence of prohibited objects, they often lack the nuance to determine if the object is actively being used. This can lead to false positives where an object is merely present in the workspace but not used for cheating. A novel approach by (Li and Li 2022) attempted to address this with a dual-camera system where a second camera mechanically pans to follow the user's gaze, but this introduces hardware complexity and potential distractions. This highlights a critical gap: the need to analyze not just the presence of objects, but the physical interaction between the user and these objects.

Temporal Analysis and Research Gaps

Most proctoring systems evaluate cheating on a frame-by-frame basis or use simple rule-based logic to aggregate flags over time. This can miss complex, temporally-dependent behaviors. A few advanced systems have begun to model these temporal patterns. (Atoum et al. 2017) computed statistical features over a time window, but a more sophisticated approach was taken by (Liu et al. 2024) using Multiple Instance Learning (MIL). Their framework treats an exam video as a "bag" of clips and learns to identify anomalous sequences corresponding to cheating, considering spatio-temporal relationships between features like eye gaze and body pose. This demonstrates the power of analyzing behavior over time rather than in discrete moments.

We find several gaps in the literature. First, few systems effectively combine object detection with hand tracking to analyze hand-object interaction, a crucial indicator of active cheating. Second, many systems rely on complex hardware or are computationally intensive. Finally, the majority of systems lack sophisticated temporal analysis to understand the context of a student's actions over time, which is essential for reducing false positives.

Methodology

Our proposed framework is a multi-stage system for real-time analysis of a candidate's behavior. As shown in Figure 1, the architecture includes: (A) System Architecture and Data Acquisition, (B) Multi-modal Feature Extraction, and (C) Cheat Probability Evaluation.

(A) System Architecture and Data Acquisition

This initial stage encompasses the physical setup and the web application responsible for capturing and distributing the video feeds.

Dual-Camera Setup We use a dual-camera configuration to minimize blind spots. A primary frontal camera captures the candidate's face, while a secondary side camera monitors the workspace, including hands and the desk area.

Web Interface An examination is delivered via a web application that captures the two video streams using WebRTC. The backend routes the "Face Cam Feed" and "Hand Cam Feed" to the respective feature extraction modules for real-time processing.

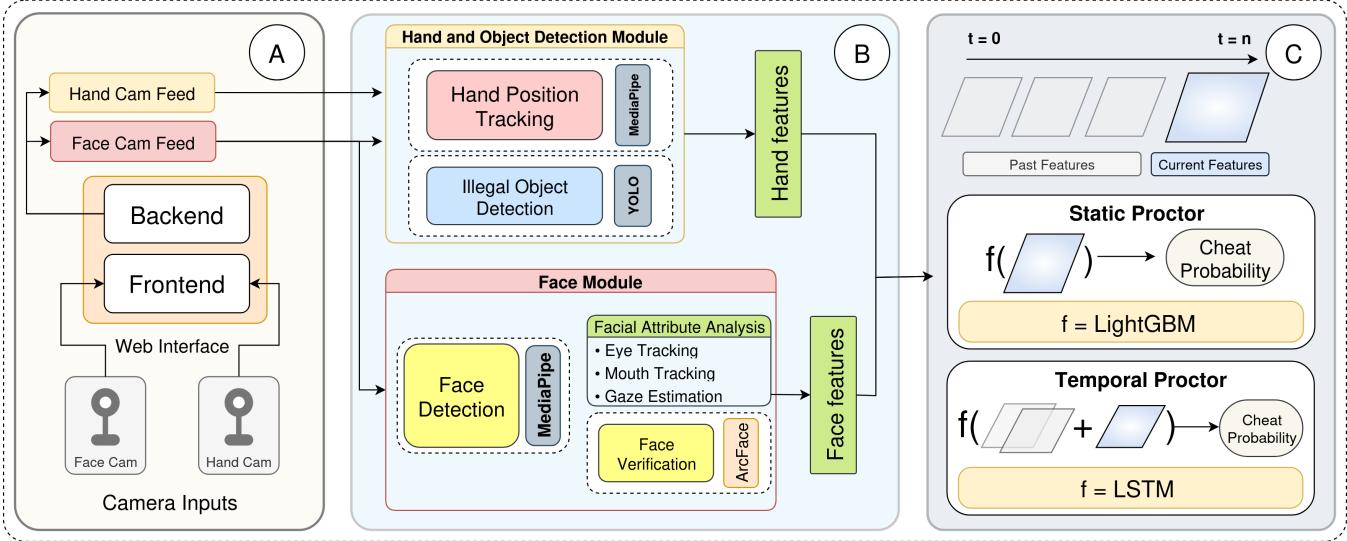


Figure 1: Architectural diagram of the AutoOEP multi-modal proctoring system. The process flows through three main stages. **(A) Data Acquisition:** A dual-camera setup captures frontal (Face Cam) and workspace (Hand Cam) video feeds, which are routed through a web interface. **(B) Multi-modal Feature Extraction:** The video streams are analyzed in parallel. The *Hand and Object Detection Module* uses YOLO to identify prohibited items and MediaPipe for hand position tracking. Concurrently, the *Face Module* uses MediaPipe for face detection and attribute analysis (eye, mouth, gaze) and ArcFace for identity verification. **(C) Cheat Probability Evaluation:** The aggregated features are processed by two models. A *Static Proctor* (LightGBM) provides a baseline prediction from a single frame, while the core *Temporal Proctor* (LSTM) evaluates sequences of features over time to generate a more robust, context-aware cheat probability score.

(B) Multi-modal Feature Extraction

This core stage processes the raw video feeds to extract a rich set of numerical features that describe the candidate’s actions and environment. It consists of two parallel modules operating on their respective camera inputs.

Hand and Object Detection Module As shown in Figure 2, this module processes the side-camera video to monitor the workspace. To train the object detection, a total of 21,200 images were assembled, comprising photographs captured under controlled examination conditions and additional samples scraped from the Open Images Dataset V4 (Kuznetsova et al. 2020). Two annotators independently labeled each image into one of six categories: *cell phone*, *chits*, *closedbook*, *headphone*, *sheet*, and *watch*. To quantify inter-annotator reliability while accounting for chance agreement, we computed Cohen’s Kappa (κ). In our study, we obtained $\kappa = 0.98$, indicating almost perfect agreement according to the Landis and Koch scale (Landis and Koch 1977).

Model Architecture and Training We fine-tuned a YOLOv11n model on our custom dataset. The model was trained for 50 epochs with a batch size of 32 on two NVIDIA T4 GPUs. The input image resolution was set to 640×640 pixels. The model is trained to detect six classes: *cell phone*, *chits*, *closed book*, *headphone*, *sheet*, and *watch*.

Hand Tracking and Interaction Analysis To differentiate between the mere presence of an object and its actual

use, we track the candidate’s hand landmarks using the MediaPipe Hands library (Lugaresi et al. 2019). To detect potential misuse of prohibited items, the distances between detected hands and prohibited items identified by YOLOv11 were calculated using their respective bounding boxes/landmarks. The distance calculation process involved the following steps:

1. Detection of prohibited items in the video frame using the YOLOv11 object detection model, which provided bounding boxes for each detected item.
2. For each detected hand and prohibited item, calculate the Euclidean distance between the centres of their respective bounding boxes using Equation 1:

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \quad (1)$$

where, (x_1, y_1) and (x_2, y_2) are the centres of the hand and prohibited item bounding boxes, respectively.

By combining MediaPipe Hands for accurate hand detection and tracking with YOLOv11 for prohibited item detection, and calculating the distance between detected hands and prohibited items, this module enables real-time monitoring and detection of potential misuse of prohibited items in controlled environments. This reduces the possibility of false positives. This capability is crucial for maintaining integrity and ensuring fair and secure examination operations.

Face Module As shown in Figure 3, this module is responsible for analyzing the frontal camera feed to verify the candidate’s identity and monitor their facial cues for behavior

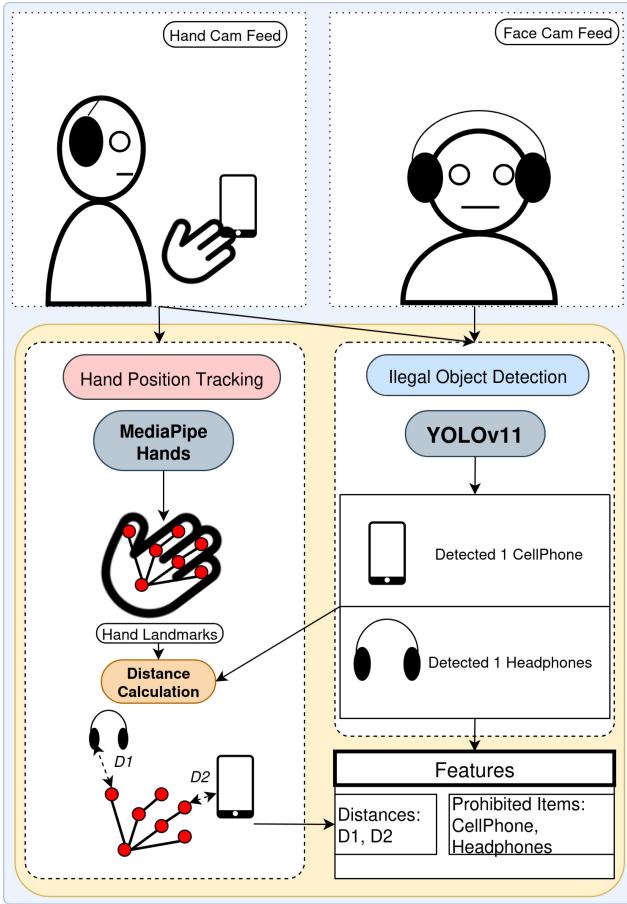


Figure 2: Workflow of the Hand and Object Detection Module. The Hand Cam feed is processed by MediaPipe Hands to extract landmarks, while a YOLOv11 (Khanam and Husain 2024) model detects prohibited items (e.g., CellPhone, Headphones) from both camera feeds. The module then calculates the distance between the hand and any detected items to generate an interaction-aware feature vector.

indicative of academic dishonesty. The module’s foundation is the MediaPipe framework (Lugaresi et al. 2019), which provides real-time face detection and extraction of 468 3D facial landmarks. These landmarks serve as the basis for all subsequent analyses. The module initially checks for the presence of a single face; deviations from this condition are flagged immediately.

Facial Attribute Analysis Using the 468 landmarks from MediaPipe’s FaceMesh, we extract a set of behavioral features designed to capture common cheating cues.

Face Verification To ensure the registered candidate is present throughout the exam, we perform continuous identity verification. The detected face is processed using the opensource DeepFace library (Serengil and Ozpinar 2024). We modified the verification pipeline to directly accept the mediapipe face landmarks from the attribute analysis step to avoid redundant computation. It employs an **ArcFace** model

(Deng, Guo, and Zafeiriou 2018) to perform the verification. This model, built on a ResNet-100 backbone, transforms the facial image into a 512-dimensional, L2-normalized embedding. We calculate the cosine similarity between the live embedding and a pre-registered reference embedding. If this similarity score falls below an empirically determined threshold, an identity mismatch is flagged, indicating a potential proxy test-taker.

- **Gaze and Head Pose Estimation:** We estimate head orientation as a primary indicator of the candidate’s focus. From a set of key 2D facial landmarks and their corresponding 3D model points, we solve the Perspective-n-Point (PnP) problem using OpenCV’s `solvePnP` algorithm (OpenCV 2023). This yields Euler angles (pitch, yaw, roll), from which we calculate an overall deviation magnitude, $r = \sqrt{\theta_x^2 + \theta_y^2 + \theta_z^2}$. This value is then used to classify the candidate’s head pose into zones of varying suspicion (white, yellow and red depending on the angle of deviation).
- **Eye Tracking:** To capture more subtle gaze shifts that are independent of head movement, we track the iris’s position within the eye socket. Using Equation 2 compute a normalized ratio based on the iris center’s distance to the eye corners:

$$\text{ratio} = \frac{\|\mathbf{c} - \mathbf{p}_{\text{right}}\|}{\|\mathbf{p}_{\text{left}} - \mathbf{p}_{\text{right}}\|} \quad (2)$$

where, \mathbf{c} is the iris center and \mathbf{p} are the eye corner landmarks. This ratio allows us to classify the gaze direction as ‘left’, ‘center’, or ‘right’, flagging excessive off-screen glances.

- **Mouth Tracking:** To detect potential communication, we monitor mouth movements by calculating the area of the polygon formed by the inner lip landmarks. The area A is computed using the Shoelace formula (Equation 3):

$$A = \frac{1}{2} \left| \sum_{i=1}^n (x_i y_{i+1} - y_i x_{i+1}) \right| \quad (3)$$

Based on this area, the mouth’s state is classified into discrete levels such as ‘closed’, ‘partially open’, or ‘fully open’, which helps in flagging potential instances of speaking.

(C) Cheat Probability Evaluation

To train and evaluate the proctoring models, we created a custom dataset by recording two videos, each approximately 10 minutes long, that simulated various exam-taking scenarios including both normal behavior and staged cheating events. These videos were split into training and testing sets with an 80:20 duration ratio. The videos were then converted to frames, and for each frame, the feature extraction modules were used to generate a feature vector. This resulted in a labeled dataset of feature sequences with a corresponding ground truth cheating outcome to train our models.

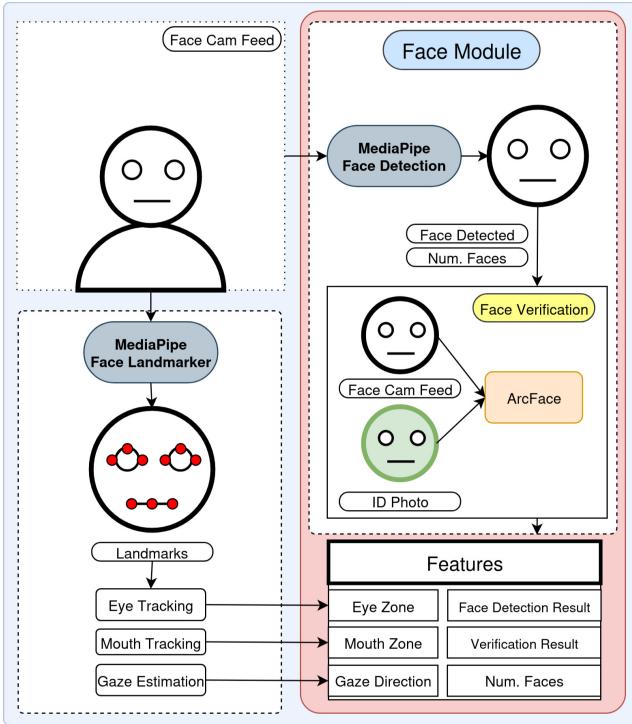


Figure 3: Workflow of the Face Module for identity and behavior analysis. The Face Cam Feed is processed in two parallel streams. One stream uses MediaPipe Face Detection and ArcFace for identity verification and face counting. The other uses MediaPipe Face Landmarker to enable behavioral tracking (eye, mouth, and gaze). The results are aggregated into a final feature vector.

Static Evaluator This model serves as a baseline, operating on a single-frame basis without considering temporal context. It uses a LightGBM (Ke et al. 2017) classifier, an efficient gradient boosting framework, to predict cheating probability based on the combined feature vector from the hand and face modules. Each feature from the face and hand modules is first preprocessed to handle potential missing values with mean imputation, followed by standardization to ensure all features are on comparable scales.

For real-time prediction, each frame’s feature vector is preprocessed using the same imputation and scaling transformations applied during training. The model then outputs a probability estimate for cheating, which is reported to the proctor interface. While this single-frame approach performs well for obvious violations, it occasionally produces false positives during rapid but legitimate movements, a limitation addressed by the temporal LSTM (Hochreiter and Schmidhuber 1997) evaluator. The static evaluator serves as both a standalone system for environments with limited computational resources.

LSTM Evaluator To incorporate temporal information, we choose a model that analyzes sequences of feature vectors over time. The LSTM (Long Short-Term Memory) model is particularly suitable for this task as the data has

Algorithm 1: Real-Time Cheating Prediction with LSTM

```

Require:  $M_{LSTM}$  (Trained LSTM model)
Require:  $S$  (Fitted feature scaler)
Require:  $w$  (Window size)
1: Initialize buffer  $B \leftarrow []$ 
2: for each incoming frame  $f_t$  do
3:    $v_t \leftarrow \text{ExtractFeatures}(f_t)$ 
4:   Append  $v_t$  to  $B$ 
5:   if  $|B| > w$  then
6:     Remove the oldest vector from  $B$ 
7:   end if
8:   if  $|B| = w$  then
9:      $B_{norm} \leftarrow S(B)$             $\triangleright$  Normalize sequence
10:     $P_{cheat} \leftarrow M_{LSTM}(B_{norm})$        $\triangleright$  Predict
    probability
11:    Report  $P_{cheat}$  to proctor interface
12:   end if
13: end for

```

long-range dependencies and temporal feature patterns.

Architecture The LSTM evaluator consists of a deep neural network architecture with an LSTM layer with a hidden size of 64. Dropout layers (rate = 0.35) after the LSTM layer to prevent overfitting. Two fully-connected layers with ReLU activation for the final classification. Finally, a sigmoid output layer producing a probability of cheating.

Feature Preprocessing Before feeding data to the LSTM model, several preprocessing steps are performed. Feature standardization is performed using a scaler to normalize each feature to zero mean and unit variance. The sequence is created with a sliding window approach, where each input consists of w consecutive frames (where w is the window size). The target label for each sequence is the cheating status of the frame immediately following the sequence.

Training Methodology The model was trained using the binary cross-entropy loss function to optimize for the cheating probability prediction. The Adam optimizer was used with a learning rate of 0.001.

Real-time Prediction During inference, the system processes frames sequentially to generate a real-time cheating probability score. A sliding window approach is used, where a buffer stores the feature vectors of the most recent frames. The process is detailed in Algorithm 1.

Experimental Results and Analysis

This section details the empirical evaluation of the AutoOEP framework. We first present the performance of the core perception modules—specifically, the Hand and Object Detection Module—followed by a comparative analysis of the static (LightGBM) and temporal (LSTM) cheat detection models as shown in Table 1.

Hand and Object Detection

The Hand and Object Detection module is a critical component of our framework, responsible for identifying pro-

Table 1: Performance Comparison of the Static and Temporal Proctoring Models on the Test Set. The superiority of the temporal model is evident across all metrics, especially in the drastic reduction of false positives.

Metric	Static (LightGBM)	Temporal (LSTM)
Accuracy	83.6%	90.7%
Precision	90.8%	87.5%
Recall	80.5%	98.4%
F1-Score	85.3%	92.7%
ROC AUC	0.926	0.989
False Positives	58	9

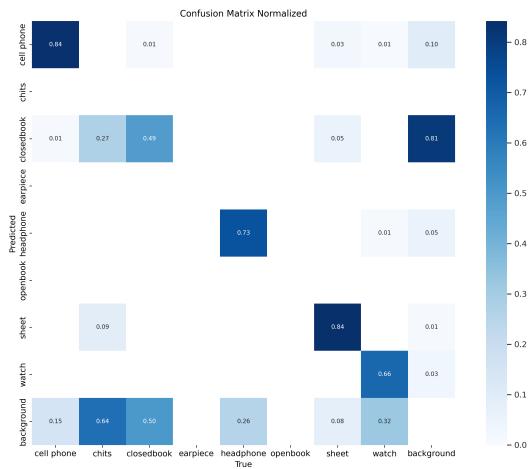


Figure 4: Normalized confusion matrix for the YOLOv11 object detection model. The diagonal represents the recall for each class, while off-diagonal cells show misclassification rates. The model performs well on distinct objects like cell phones but struggles to differentiate items like closed books from the background.

hibited items in the examinee’s workspace. We evaluated our fine-tuned YOLOv11 model after 50 epochs of training. Overall, the model achieved a mean Average Precision at 50% IoU (mAP@.5) of 0.571 and a more stringent mAP@.5:.95 of 0.371. The global precision and recall across all classes were 75.9% and 54.0%, respectively.

For a more granular, per-class analysis, we present the normalized confusion matrix in Figure 4. The matrix highlights both the strengths and weaknesses of the model.

Strengths: The model demonstrates high efficacy in identifying distinct objects. It achieves an excellent recall of 84% for both cell phone and sheet. It also performs well in detecting headphone and watch, with a recall of 73% and 66%, respectively. This indicates strong performance on the most common and critical items used by an examinee to cheat.

Weaknesses: The model struggles with objects that are more visually ambiguous or can easily blend into the background. The performance on closedbook is notably poor, with a recall of only 49%. The confusion matrix reveals that 81% of closedbook instances are misclassified as background, suggesting the model has difficulty distinguishing

book covers from desk surfaces. Similarly, a significant portion of chits (scraps of paper) are confused with the background (64%). Furthermore, this model frequently misidentifies parts of the background as objects, particularly as closedbook (50%) and watch (32%), contributing to false positives.

In summary, while the object detection model is highly effective for key items, future work could focus on improving its ability to differentiate smaller, less distinct objects from background clutter, potentially by using a larger, more varied training dataset.

Static Proctor

The performance of the static, frame-by-frame proctoring model was evaluated using a LightGBM classifier. This model was selected after comparing it with random forest (Breiman 2001) and XGBoost (Chen and Guestrin 2016). To address the inherent class imbalance in the proctoring dataset, the training data was augmented using the borderline-SMOTE technique. The comprehensive results of the model on the test set are presented in Figure 5.

The feature importance analysis (top-left in Figure 5) confirms the effectiveness of our proposed modules. The single most important feature for the model is the radial distance, which measures the angle of deviation of the candidate’s head from the front camera. Other high-importance features include the iris ratio, mouth area and the distance between illegal objects and the candidate’s hand.

The model’s overall discriminative power is passable, as shown by the Receiver Operating Characteristic (ROC) curve, which achieves an Area Under the Curve (AUC) of 0.926. This indicates the ability to distinguish between cheating and non-cheating instances across most but not all classification thresholds. The Prediction Probability Distribution plot further supports this, showing a clear separation between the predicted probabilities for the two classes.

The confusion matrix, calculated at an optimized 0.46 probability threshold, reveals the model’s performance. The model achieves a recall of 80.5% for the cheating class (correctly identifying 571 out of 709 cheating instances) and produces only 58 false positives. This results in a precision of 90.8% and an overall accuracy of 83.6%. Despite this good accuracy, the trade-off highlights a key challenge: without temporal context, normal movements can occasionally be misinterpreted as suspicious, leading to a higher rate of false positives.

Temporal Proctor

To address the limitations of the static model, we evaluated an LSTM-based temporal model that analyzes sequences of data over a window of 15 frames. This approach allows the model to learn from the context of actions rather than isolated moments.

Figure 6 shows the results of the Temporal model which indicates a marked improvement over the static model. The model’s discriminative power remains excellent, achieving a Receiver Operating Characteristic (ROC) Area Under the Curve (AUC) of 0.989, which indicates a very strong ability to distinguish between the two classes.

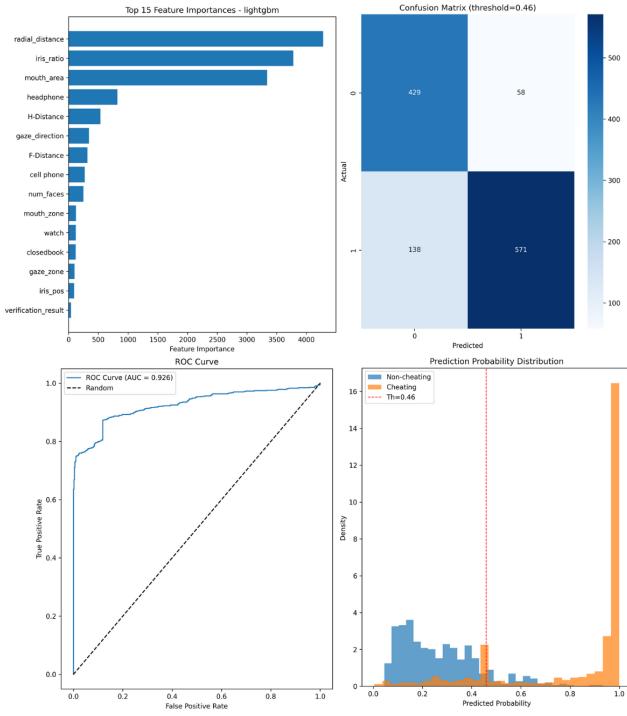


Figure 5: Performance metrics for the static LightGBM proctoring model. Clockwise from top-left: Top 15 Feature Importances, Confusion Matrix, Prediction Probability Distribution and ROC Curve.

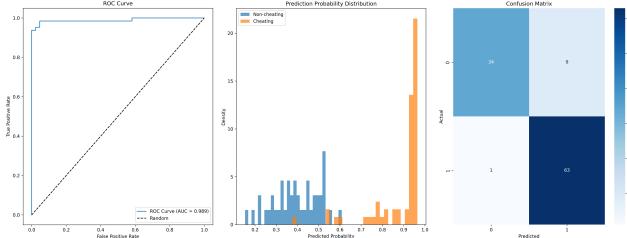


Figure 6: Performance metrics for the temporal LSTM proctoring model. From the left: ROC Curve, Prediction Probability Distribution and Confusion Matrix.

The most significant improvement is seen in the confusion matrix. The LSTM model achieves a high overall accuracy of 90.7%. Most notably, it demonstrates an extremely strong recall of 98.4%, successfully identifying 63 out of 64 cheating instances in the test set. While achieving this near-perfect detection rate, it dramatically reduces the number of false positives from 58 in the static model to just 9. This results in a solid precision of 87.5% and a balanced F1-score of 92.7%. This substantial reduction in false accusations, while maintaining best-in-class detection of actual cheating, underscores the superiority of the temporal approach. By understanding the sequence of events, the LSTM can effectively differentiate between momentary, innocuous movements and sustained, deliberate patterns of suspicious

behavior of the examinee.

System Performance and Real-Time Capability

We evaluated the computational performance of the AutoOEP framework. All performance benchmarks were conducted on a system on CPU (Ryzen 3500U) with 8GB RAM. The average inference time for each core component of the framework is detailed in Table 2.

Table 2: Component performance breakdown (avg. latency per frame).

Component	Time (ms)
Face Module (Extraction)	421
Hand Module (Extraction)	193
Temporal Proctor (LSTM)	5.1
Static Proctor (LightGBM)	2.7

The analysis reveals that the **Face Module is the primary computational bottleneck**. This resulted in a final processing speed of **2.37 frames per second**.

Conclusion

In this paper, we introduced AutoOEP, a multi-modal, dual-camera framework designed to address the critical challenges of accuracy and fairness in automated online exam proctoring. We demonstrated that by moving beyond simple rule-based systems and leveraging context-aware analysis, it is possible to create a more robust and reliable proctoring solution. Our approach uniquely combines facial cue analysis, prohibited object detection, and hand-object interaction tracking. The empirical results compellingly show that our temporal LSTM model with an accuracy of 90.7% and an F1-score of 92.7%, significantly outperforms static, frame-by-frame analysis by effectively understanding the sequence and context of an examinee's behavior.

The significance of this work lies in two key contributions. First, the introduction of the hand-object interaction module provides a more nuanced method for detecting cheating than simple object presence, directly addressing a major gap in existing systems. Second, our use of a temporal model drastically reduced false positives compared to the static baseline, highlighting the importance of temporal context in creating systems that are not only effective but also fair to the student. By achieving these results with commodity webcams, AutoOEP presents a practical and scalable solution for educational institutions.

Despite the promising results, we acknowledge several limitations that open avenues for future research. The object detection model, while effective for key items like cell phones, struggled with visually ambiguous objects such as closed books and notes against cluttered backgrounds. Future work should focus on enhancing this module, potentially by augmenting the training dataset or exploring more advanced detection architectures. Furthermore, the current framework is purely vision-based; integrating an audio processing module to detect and analyze suspicious speech

would provide another valuable layer of security. Finally, while our system performed well on a custom dataset, large-scale deployment in live examination settings is necessary to validate its robustness and usability in real-world conditions.

Ultimately, AutoOEP represents a significant step towards creating intelligent, accessible, and trustworthy systems capable of safeguarding academic integrity in the ever-expanding landscape of online education.

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