AISENTINEL: A Real-Time Automated Exam Proctoring System Using Deep Learning on Edge Device

A Capstone Project Presented to the Faculty of the College of Engineering,

University of Southeastern Philippines,

Bo. Obrero, Davao City

In Partial Fulfillment of the Requirement for the Degree

Bachelor of Science in Electronics Engineering

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October 2025

Chapter I

Introduction

1.1 Background of the Study

Academic integrity remains one of the core pillars of education, with examinations serving as a primary measure of learning and professional competence. However, academic dishonesty, particularly cheating during examinations, has become increasingly prevalent worldwide, especially during and after the COVID-19 pandemic [1]. In China, between 15.4% and 51.7% of students admitted to academic dishonesty [2], while in Andhra Pradesh, India, 93.4% of students reported cheating [3]. Similar trends have been observed in the Philippines, where access to mobile phones and the internet has enabled new cheating strategies. Aguilar (2021) found that 25% of first-year and up to 57% of second-year students admitted to academic misconduct [4]. These numbers show that cheating is not only widespread but also evolving in sophistication, making traditional supervision increasingly inadequate.

In the Philippine context, surveys indicate that over one-third of college students have engaged in cheating during face-to-face or online examinations [4], [13]. Institutions such as CHED and DepEd have issued memoranda promoting academic honesty [14], [15], yet instructors continue to face challenges in detecting subtle or coordinated cheating strategies, especially in large classrooms [16]. A study involving over 26,000 students in Region XI revealed that 70% of students who cheated were never caught [17]. Although many schools have CCTV systems, these are primarily for security and lack intelligent analytics, making them ineffective for detecting quick or discreet cheating behaviors [18].

To address these gaps, technological interventions have been developed to support academic integrity. Deep learning–based proctoring systems and object detection models have shown potential to enhance exam monitoring by enabling real-time behavioral detection. Among these, the You Only Look Once (YOLO) architecture has emerged as one of the most efficient solutions because of its single-stage detection framework, combining speed and accuracy in real-time applications [5].

Recent advancement in deep learning, particularly in real-time object detection, have paved the way for more effective monitoring systems. The latest iteration of You Only Look Once (YOLO) architecture, YOLOv11 provides significant improvements in accuracy and detection speed compared to its predecessors. In controlled experiments, YOLOv11 achieved a mean Average Precision (mAP) of 0.991 at a 0.5 confidence threshold and real-time performance of 30 FPS across multiple cheating behavior classes (e.g., leaning to copy, looking around, talking, passing notes), surpassing the accuracy of previous YOLO versions [6]. This demonstrates its strong potential as a specialized tool for proctoring and academic integrity protection.

Other deep learning approaches have also shown promise. Holi et al. used Haar cascades and LBPH to detect suspicious behavior with 92.3% accuracy [7], while Liu et al. employed 3D CNNs for spatio-temporal feature extraction with 83.8% accuracy [8]. Kaddoura's work further demonstrated the feasibility of deep learning for real-time cheating detection [10]. However, most existing systems rely on cloud processing, which introduces latency, bandwidth demands, and privacy concerns. Many also lack sufficient safeguards for data handling, underscoring the need for locally deployed, privacy-conscious solutions [12].

In summary, despite existing institutional efforts and emerging technological tools, no locally developed, low-cost, and privacy-conscious real-time proctoring system has been implemented in the Philippine classroom setting. This context highlights an urgent need for such systems that can operate efficiently without compromising privacy. To address this gap, the present study proposes AISENTINEL, an automated exam proctoring system utilizing YOLOv11 capable of detecting cheating behaviors through real-time video analysis on an edge device, while storing only short activity clips to maintain accountability with minimal data collection. All procedures will follow institutional ethical standards, including informed consent and formal ethics approval. This aligns with recent global incidents of exam cheating, such as mobile phone use in UK exams [20] and cheating cases among PNPA cadets in the Philippines [21], reinforcing the urgency for robust proctoring interventions.

1.2 Statement of the Problem

This study aims to address the monitoring of academic dishonesty during face-to-face examinations. Specifically, this study will answer the following questions:

1. How can a real-time system detect suspicious behaviors such as passing papers, tilting heads, hands under table, or using phone or unauthorized notes during examinations?
2. How can a portable edge-device system be implemented to capture live video, trigger immediate alerts, and record short video clips of detected cheating activities?
3. How accurate and reliable is the proposed system in detecting cheating behaviors under controlled face-to-face examination conditions?

1.3 Objectives of the Study

This study aims to address the challenges of monitoring academic dishonesty in face-to-face examinations by developing AISENTINEL, a real-time automated exam proctoring system. Specifically, it seeks to:

1. Develop a real-time cheating detection model using YOLOv11, focused on detecting 5 defined suspicious behaviors.

2. Implement a portable edge-device system using Raspberry Pi 5 with Raspberry Pi AI HAT+ 26 TOPS that captures live video, triggers immediate alerts, and records short evidence clips of detected cheating events.
3. Evaluate the accuracy, precision, and reliability of the developed system in controlled examination settings to determine how it supports human invigilators and upholds academic integrity.

1.4 Significance of the Study

The findings of this study may be utilized to promote fairness, integrity, and efficiency in the administration of face-to-face examinations. It can stimulate additional studies on developing real-time monitoring tools for academic settings, exploring the integration of edge-based technologies in low-cost educational technologies, and providing new directions for advancing academic honesty through digital systems. The following are the stakeholders who may potentially benefit from this study.

Students. This study seeks to establish a fairer examination environment where students' grades reflect their individual efforts and knowledge. By reducing opportunities for dishonest practices, the system ensures that students' academic performance is measured more accurately, which may also strengthen trust in institutional grading systems.

Teachers and Invigilators. For teachers and invigilators, the system offers a practical solution to the challenges of monitoring large examination rooms. It provides an additional layer of assistance in detecting cheating behaviors, thereby reducing their workload and allowing them to focus on instruction and academic guidance rather than extensive surveillance.

University Administration. The system provides a reliable means of documentation through short video clips, offering credible evidence to support the enforcement of academic integrity policies. This contributes to institutional credibility by ensuring that assessments remain objective and trustworthy, which in turn helps maintain the quality of education provided.

Research and Technology Community. This study contributes to the broader field of educational technology and artificial intelligence by demonstrating the application of real-time, edge-based AI systems in practical, low-cost academic settings. The findings and methodologies may serve as a foundation for future innovations in automated monitoring, smart classroom technologies, and the promotion of ethical standards in education.

1.5 Scope and Limitations of the Study

This study focuses on achieving three key objectives: (1) detecting suspicious behaviors during examinations such as passing papers, head tilting, hands under table, cellphone, and cheat sheet, (2) implementing a real-time proctoring system that integrates a Raspberry Pi 5 with a Raspberry Pi AI HAT+ 26 TOPS and cameras for monitoring, and (3) recording short video clips with timestamps whenever cheating behavior is detected to serve as evidence for review. These aspects aim to strengthen the integrity of academic assessments by providing automated, real-time support to human proctors. The system utilizes the YOLOv11 object detection model, optimized for real-time execution on edge devices to ensure accuracy and responsiveness.

The data-gathering process will be conducted in a controlled simulation room designed to approximate a standard Philippine classroom with dimensions of 7 m × 9 m and an estimated seating capacity of 40–50 students under normal conditions. However, in line with post-pandemic DepEd and DOH guidelines for safe classroom layouts, this prototype will arrange seats with at least 1 meter of spacing between chairs to reduce occlusions and improve camera coverage. For evaluation purposes, the simulation will involve 20 or fewer students with an average exam duration of 1 hour and 30 minutes. The monitoring setup will employ two strategically positioned cameras to provide a multi-angle view of the room, ensuring that suspicious behaviors are captured from multiple angles. Each recorded cheating event will generate a video clip stored locally with timestamps for administrative review.

The scope of this study is limited to visual cheating behaviors detectable within the camera's field of view, particularly around each student's tables. The system can identify cellphones, notes, passing of papers, hands under table, and abnormal head movements. However, it cannot reliably distinguish cheat sheets that mimic the official questionnaire in size, nor can it capture subtle, non-object-based behaviors such as hand signals. Moreover, as this is a prototype implemented in a controlled simulation environment, results may differ from those in larger or varied real-world classroom settings.

1.6 Definition of Terms

Academic Integrity – Refers to the adherence to ethical principles and honest practices in academic work, including exams, assignments, and research. Violations include cheating, plagiarism, and other forms of dishonest behavior [1], [2].

Academic Dishonesty – Refers to acts that breach academic integrity, such as using unauthorized resources, falsifying information, or presenting another's work as one's own [1].

Proctoring System – Refers to the method or framework, whether human-based or technology-assisted, used to supervise examinations and ensure compliance with academic integrity standards [3].

Cheating Detection – Refers to the process of identifying behaviors or actions that indicate dishonesty during examinations, such as head tilting, gaze diversion, or use of prohibited devices [3], [4].

Object Detection – Refers to the computer vision task of identifying and locating objects in digital images or video streams by classifying and drawing bounding boxes around them [5].

You Only Look Once (YOLO) – Refers to a family of deep learning–based object detection algorithms designed for real-time vision tasks due to their speed and accuracy [6].

YOLOv11 – Refers to the latest iteration of the YOLO object detection family, incorporating an enhanced backbone network, improved feature pyramid structures, and attention mechanisms to achieve higher accuracy and efficiency in real-time detection tasks [6].

Deep Learning – Refers to a subset of machine learning that uses multi-layered neural networks to automatically learn hierarchical features from large datasets [8].

Edge Device – Refers to a computing unit, such as a Raspberry Pi or Raspberry Pi AI HAT+ 26 TOPS, that performs data processing near the data source instead of relying on cloud servers [9].

Edge TPU – Refers to Google's Tensor Processing Unit designed to accelerate deep learning inference efficiently on edge devices with low latency and power consumption [10].

Raspberry Pi AI HAT+ 26 TOPS – A hardware add-on board with a built-in Hailo-8 neural network inference accelerator that delivers up to 26 TOPS, enabling fast and efficient edge-AI processing for applications such as robotics, security, home automation, and camera/video tasks on Raspberry Pi 5 [11].

Chapter II

Review of Related Literature and Theoretical Framework

This chapter presents related literature and studies that provide context for the issue of academic dishonesty in examinations. It reviews both global and local perspectives to establish the prevalence of cheating and the challenges it poses in maintaining academic integrity. The discussion highlights existing methods of monitoring and their limitations, allowing the identification of research gaps relevant to the present study. By examining these works, the chapter provides a foundation for the study's objectives, methodology, and conceptual framework.

2.1. Related Literature

Academic dishonesty, particularly in examinations, has long been a concern for educational institutions. Cheating undermines the credibility of academic assessments and threatens the integrity of educational outcomes. Traditional proctoring methods, such as in-person invigilation, seating arrangements, and strict exam protocols, have historically been the primary mechanisms for preventing such misconduct. While these measures can reduce opportunities for cheating, they have not eliminated the problem entirely. Global and local research continues to report significant instances of academic dishonesty, indicating that even well-established proctoring practices face persistent challenges. The following subsections present an overview of the prevalence of cheating in examinations and the effectiveness and limitations of traditional monitoring approaches.

2.1.1. Prevalence of Academic Dishonesty in Examinations

Academic dishonesty remains a pressing issue across higher education worldwide. Studies have shown that cheating behaviors continue to rise, with large-scale surveys confirming that misconduct is widespread across different regions and not confined to a single cultural or institutional context [1][2][3]. For instance, Liu and Alias [2] found high prevalence rates of dishonesty among Chinese undergraduates, with demographic factors such as gender, year level, and academic performance influencing behavior. Similarly, Anitha and Sundaram [3] reported that common practices, such as copying during exams, unauthorized collaboration, and plagiarism, are often driven by peer pressure, academic stress, and insufficient deterrent measures. These findings indicate that systemic pressures and high-stakes assessments contribute to dishonesty as a coping mechanism rather than an isolated act.

In the Philippine context, research highlights that cheating in examinations is equally pervasive. Aguilar [4] emphasized that academic dishonesty is deeply rooted in assessment culture, often normalized among students in both formal and informal ways. Cleto [24] further documented multiple forms of misconduct, including impersonation, plagiarism, and the use of prohibited materials during exams, underscoring how dishonesty adapts to various environments. Although some recent studies explore online and blended learning contexts [14][15], the persistence of cheating in traditional, face-to-face examinations reflects that misconduct is not merely a byproduct of digital platforms but an enduring challenge in physical classrooms as well.

Taken together, these studies demonstrate that academic dishonesty is a global and local concern with diverse manifestations. In particular, the Philippine experience shows that face-to-face exam cheating persists despite institutional regulations, often enabled by cultural acceptance and systemic academic pressures. This underlines the urgent need for effective monitoring and proctoring mechanisms that can uphold the integrity of in-person examinations.

2.1.1.1 Common Cheating Practices in Philippine Universities

In the Philippine academic context, studies indicate that cheating is not only prevalent but also adaptive to changing classroom environments. Aguilar [4] reported that students often engage in practices such as copying answers, passing notes, and using unauthorized materials during examinations. These behaviors are reinforced by peer acceptance, institutional leniency, and the perception that cheating is a normalized coping strategy within competitive academic settings. Expanding this view, Amorado and Vilchez [19] described the phenomenon as a “pedagogy of fraud,” highlighting how students develop creative methods of dishonesty—such as hidden notes, subtle signaling, or collaborative deception—particularly in environments where supervision is perceived as inadequate. These findings reveal that cheating in the Philippines is not merely an individual act of misconduct but part of a broader academic culture shaped by both social and institutional factors.

2.1.1.2 Implications for Academic Integrity and Institutional Reputation

The persistence of cheating practices carries significant risks for academic institutions. Ives and Cazan [1] argued that the rise of misconduct, amplified by the post-pandemic academic landscape, undermines trust in educational systems and diminishes the credibility of qualifications. Similarly, Lisao [17] noted that emerging challenges, such as the misuse of generative AI, further threaten the integrity of assessments, requiring proactive institutional responses. Reports from international and local media underscore these risks: the use of unauthorized devices and disruptive behaviors has been flagged as a growing concern globally [20], while cases in the Philippines—such as the expulsion of cadets from the Philippine National Police Academy for exam cheating—demonstrate the reputational consequences of misconduct [21].

Beyond reputational harm, scholars and educators emphasize that examinations are foundational for ensuring fairness and academic progression [26][27]. When dishonesty compromises this process, institutions risk eroding public trust, devaluing degrees, and weakening the broader culture of meritocracy. These implications highlight the urgent need for more effective monitoring mechanisms to safeguard academic integrity in higher education.

2.1.2. Traditional Proctoring Approaches

Manual invigilation remains the most widely practiced and historically trusted method for monitoring examinations in classroom settings. For decades, academic institutions have relied on the presence of human invigilators to safeguard the fairness of assessment environments. In this approach, one or more proctors are physically present in the examination venue to enforce regulations, deter dishonest practices, and provide immediate intervention when irregularities occur [40][41]. Unlike automated or remote proctoring solutions, manual proctoring emphasizes direct observation, where the invigilator's judgment and attentiveness play a central role in ensuring integrity.

2.1.2.1. The Multifaceted Role of the Human Proctor

The role of the human proctor extends beyond mere surveillance; it embodies a complex, multi-sensory responsibility that integrates deterrence, situational awareness, and procedural management. The physical presence of a proctor establishes a formal examination atmosphere, which psychologically discourages dishonest behavior by invoking the principles of deterrence theory [68][69]. Recent empirical studies reveal that visible monitoring and social presence increase students' perceived risk of detection, thereby reducing tendencies toward academic misconduct [68]. This psychological effect underscores that deterrence in proctored settings functions not only through actual observation but also through the perceived probability of being caught [69].

Furthermore, human proctors exhibit dynamic situational awareness by interpreting a broad spectrum of behavioral cues that may indicate dishonesty. Their vigilance extends beyond overt acts such as whispering or passing notes, encompassing subtle indicators like unusual fidgeting, wandering eyes, or excessive attention toward neighboring students [43]. They are also familiar with local cheating strategies, such as the use of *kodigo* or hidden notes, which require contextual understanding and cultural familiarity to detect effectively [4][48]. In addition to these cognitive and perceptual tasks, proctors also fulfill administrative roles by distributing examination materials, enforcing time limits, and clarifying procedural inquiries throughout the testing period [40]. Collectively, these functions illustrate that human proctoring involves continuous cognitive engagement, rapid situational judgment, and interpersonal management, forming a multifaceted system of exam integrity maintenance.

2.1.2.2. Inherent Limitations and Systemic Vulnerabilities

Despite its enduring importance, manual proctoring suffers from several inherent limitations that challenge its effectiveness and consistency. One significant constraint arises from the *vigilance decrement* phenomenon, a well-documented psychological effect in which attention and detection performance decline during prolonged, monotonous surveillance tasks [70][71]. Studies in human factors and cognitive psychology demonstrate that individuals engaged in sustained monitoring show reduced sensitivity and increased lapse rates over time, suggesting that proctors may miss critical behavioral cues as examinations progress [70].

Another limitation concerns scalability and resource intensity. In large lecture halls or mass testing environments, a single proctor may be tasked with supervising dozens of students, making comprehensive observation impractical and increasing the likelihood of oversight [16][41]. Additionally, human proctoring is subject to variability and bias; enforcement decisions often depend on the proctor's subjective interpretation of student behavior, leading to inconsistencies in identifying or reporting suspected cases of misconduct [72]. This subjectivity undermines the fairness and reliability of manual invigilation systems. Moreover, human vision and positioning introduce further vulnerabilities—limited fields of view and physical obstructions create blind spots that can be exploited by examinees [18].

Finally, the absence of objective documentation compounds these challenges. Proctors who witness suspicious actions frequently lack concrete evidence to substantiate their claims, making it difficult to pursue disciplinary measures. Lancaster and Clarke [73] emphasized that relying solely on human testimony is procedurally weak, advocating for the integration of digital or forensic evidence to corroborate observations. Collectively, these limitations highlight the systemic vulnerabilities of traditional invigilation methods and reinforce the need for technologically assisted or hybrid proctoring systems to ensure equitable and verifiable exam administration.

2.2. Deep Learning and Computer Vision in Exam Proctoring

The rapid advancement of artificial intelligence has introduced new opportunities for enhancing the reliability and efficiency of exam monitoring systems. In particular, deep learning and computer vision techniques have emerged as powerful tools for detecting academic dishonesty, offering automated solutions that address the inherent limitations of manual proctoring, such as subjectivity, fatigue, and restricted visibility. By enabling the automated recognition of suspicious behaviors, these technologies reduce reliance on human supervision while maintaining fairness and integrity in assessment environments. The following subsections discuss the role of machine learning, and later deep learning, in detecting behavioral anomalies during examinations.

2.2.1. Application of Machine Learning in Behavior Detection

The application of machine learning (ML) and computer vision techniques has gained considerable traction in the field of exam proctoring as a response to the limitations of traditional, human-only supervision. Early approaches primarily relied on handcrafted feature extraction and conventional computer vision methods such as Haar cascades and Local Binary Patterns Histograms (LBPH), which were used for tasks like face and gesture recognition [29]. These techniques provided a foundational basis for detecting suspicious activities, yet they suffered from limited robustness when applied to complex, real-world exam environments where variations in lighting, head movement, and occlusion were common [38].

With advancements in artificial intelligence, a transition toward deep learning models, particularly convolutional neural networks (CNNs), has significantly improved behavior detection accuracy. CNN-based approaches allow for automatic feature extraction and can capture subtle irregularities in student activity, such as repeated head tilts, unusual hand movements, or attempts to consult hidden materials [29][30]. For instance, Kaddoura (2022) proposed a real-time cheating detection framework using deep learning, demonstrating enhanced precision and efficiency in identifying dishonest behaviors compared to earlier methods [10]. Similarly, Erdem and Karabatak (2025) emphasized the application of both ML and DL algorithms for monitoring offline examinations, underlining their potential to complement traditional invigilation and strengthen integrity safeguards.

Beyond individual models, recent research has explored integrated ML frameworks that combine multiple algorithms to improve adaptability across educational contexts. Such frameworks have been applied in the detection of “unusual academic activities,” showing promising results in capturing a wider range of behavioral anomalies with minimal human intervention [29][30]. Overall, the evolution from handcrafted features to deep learning-based detection reflects a paradigm shift, where automated proctoring systems increasingly harness computer vision to recognize nuanced behavioral patterns and thereby enhance the reliability of exam monitoring.

2.2.2. Evolution of YOLO for Real-Time Proctoring

The You Only Look Once (YOLO) architecture has become a cornerstone in automated proctoring due to its single-stage detection framework, which uniquely balances high speed with accurate, real-time identification of objects and activities within video streams [5]. This advantage has made successive versions of YOLO (v4–v11) particularly relevant for proctoring applications, where immediate detection of suspicious behaviors is essential.

The evolution of YOLO demonstrates a clear trajectory of improvement tailored to the challenges of the examination hall. Earlier versions established the feasibility of the approach, while later iterations introduced significant enhancements. For instance, Zuo et al. [5] enhanced YOLOv8 with attention mechanisms, achieving high accuracy in detecting behaviors such as head tilting and hand movements, though their work also highlighted limitations with occluded objects. Similarly, Holi et al. [67] demonstrated the effectiveness of YOLO in intelligent offline monitoring systems, confirming its capability to flag cheating behaviors in real time in classroom environments.

The versatility of the YOLO family is further evidenced by its application in related academic monitoring tasks. Adhantoro et al. [8], for example, applied YOLO models in conjunction with facial recognition to strengthen behavioral analysis. Collectively, these studies, along with reviews and meta-analyses [32][33], validate YOLO's superiority over traditional computer vision techniques, consolidating its place as a key tool for real-time academic integrity monitoring. This progression of YOLO versions provides the critical foundation upon which the latest iteration, YOLOv11, builds to offer a decisive advantage for next-generation proctoring systems.

2.2.2.1 Related Studies Matrix

Table 1. Related Study Matrix on Cheating Detection Systems

Year	Title	Description	Identified Gaps/ Recommendations
2023	Automatic Cheating Detection In Exam Hall	This study developed a real-time cheating detection system using CCTV feeds. It combined the YOLOv3 object detection model with the ShuffleNet architecture to	The 88.03% accuracy indicates room for improvement, particularly in reducing false positives/negatives. The

		improve computational efficiency for live analysis. The system was trained on a locally produced dataset of classroom videos and was designed to alert administrators upon detecting unauthorized materials or devices. **Model**: YOLOv3 with ShuffleNet **Result**: Achieved a detection accuracy of 88.03% in a classroom setting.	use of the outdated YOLOv3 model limits performance compared to newer architectures. Recommendations include adopting more advanced models (e.g., YOLOv8+), integrating multi-modal data (e.g., audio), and implementing privacy-preserving techniques for broader ethical adoption.
2022	Advances in Contextual Action Recognition: Automatic Cheating Detection	This research introduced a framework for classifying cheating actions like paper passing and phone use. It evaluated five feature extraction methods (BRISK, MSER, HOG, SURF,	The reliance on traditional ML with handcrafted features (SURF) is less robust than modern deep learning for complex behavior recognition. The dataset was limited in

	Using Machine Learning Techniques	SURF+HOG) with a multi-class SVM classifier on a custom video dataset. **Model:** Traditional ML (SVM with feature extractors) **Result:** The SURF feature extractor achieved the highest average accuracy of 91%, though performance varied significantly across different cheating behaviors.	scope and diversity. Future work should utilize deep learning models, expand the dataset to include varied lighting, camera angles, and environmental conditions to improve generalizability.
2023	A Video-based Detector for Suspicious Activity in Examination with OpenPose	This study uses video from classroom exams and employs OpenPose (multi-person pose estimation) + CNN classifier to detect suspicious behavior including exchanging of objects between students (passing of papers) and abnormal hand movements.	Focused mainly on object exchanges; lacked modules for phones, cheat sheets, or head tilt. No YOLO or multi-camera setup. Future studies should integrate object detection (YOLO) and head-pose estimation using multiple cameras to capture subtle cheating behaviors.

		Model: OpenPose + CNN **Result:** Successfully identified “object exchange / passing papers” and raised alerts for such behavior under typical classroom video settings.	
2024	Cheating Detection in Examinations Using Improved YOLOv8 with Attention Mechanism	This study introduced an improved YOLOv8 model with an Efficient Channel Attention (ECA) mechanism to detect cheating behaviors in examination halls. It analyzed surveillance video frames for suspicious actions such as passing papers, using hidden materials, and looking away from the exam sheet. **Model:** YOLOv8 + ECA Attention Mechanism **Result:** 82.71 % detection	Accuracy remains moderate and limited to visible actions. It does not detect head tilting or phone use under the table. Uses only one camera angle. Future work should integrate pose estimation (head tilt), multi-camera fusion, and sequence-based recognition to capture subtle or occluded behaviors.

		accuracy with real-time inference on standard GPUs	
2023	A Comparative Study of Deep Transfer Learning Algorithm for Cheating Detection in the Exam Based on Surveillance Camera Recording	Analyzes surveillance video of exam halls to detect cheating behaviors such as using notes/book, talking, using phone, asking a friend. Uses transfer learning architectures + LSTM to capture temporal dependencies. **Model:** Deep Transfer Learning (e.g., ResNet50V2 etc.) + LSTM. **Result:** Accuracy ~ 0.964, MCC ~ 0.971 for detection of suspicious cheating activities.	Strong performance but likely on behavior that is clearly visible; subtler or occluded behaviors (phones and cheat sheet usage, small object passing) not part of dataset. Also many model do not handle multi-camera fusion. Real-time deployment details are limited.

Table 1. Related Study Matrix on Cheating Detection Systems

2.3. Challenges and Limitations of Automated Cheating Detection

Despite the promise of deep learning and computer vision in exam proctoring, the deployment of these technologies is constrained by several technical, practical, and contextual challenges. Unlike traditional invigilation, where human judgment adapts dynamically to nuanced behaviors, automated systems rely on predefined models and datasets that are often unable to capture the full complexity of classroom cheating practices. Limitations in behavior detection, dataset creation, and object differentiation introduce risks of misclassification, reduced accuracy, and impractical implementation requirements. Acknowledging these constraints is crucial, as it frames the rationale for narrowing the scope of this study to specific behaviors and conditions that are both practically observable and technically feasible to detect using current tools and resources.

2.3.1. Complexity of Multi-Behavior Detection

While the potential of automated systems to detect multiple cheating behaviors simultaneously is well recognized, current technologies face notable challenges in addressing such complexity. Deep learning models like YOLO are highly effective in single-object detection, yet extending them to monitor overlapping or subtle behaviors (e.g., whispering, eye movement, or hand signals) demands significant computational power and advanced multimodal integration [50][51]. Existing research underscores how accuracy decreases as the number of concurrent behaviors increases, as the system must parse multiple layers of visual information in real time [52][53].

Given these conditions, this study focuses on behaviors that are both frequent in classroom examinations and visually distinguishable: use of mobile phones, head tilting, passing of papers, and handling of cheat sheets (kodigo). These actions are practical starting points because datasets and detection frameworks already exist to support them [54]. More intricate behaviors remain a worthwhile area for future research, though their inclusion in this study would require resources and expertise that exceed the available scope.

2.3.2. Dataset Creation Constraints

The performance of deep learning models is closely tied to the availability of large and diverse datasets. Robust training typically requires thousands of annotated images captured under different conditions, yet such datasets are scarce, especially in the context of face-to-face examinations [55]. Publicly available datasets, while useful, often reflect international settings and lack alignment with the specific conditions found in Philippine classrooms [56].

Environmental variables such as lighting, seating layouts, camera perspectives, and even the color of armchairs can greatly influence model accuracy [53]. Acknowledging these challenges, this study narrows its dataset to settings that are contextually relevant—classrooms using the commonly available white armchairs in the Philippines. Moreover, data collection is limited to 20 students per session, a scope that balances feasibility with the need for controlled experimentation [50][57]. Broader datasets remain a goal for future efforts, but this focused approach provides a realistic foundation for developing and evaluating the model.

2.2.3. The YOLOv11 Advantage for Proctoring

The limitations and recommendations systematically documented in the Related Studies Matrix (Table 1) create a clear mandate for a technological leap in automated proctoring. The consistent themes of moderate accuracy, poor performance on occluded or subtle behaviors, and the use of superseded models underscore the need for a more robust detection framework. The YOLOv11 architecture is specifically engineered to address these exact shortcomings, positioning it as the optimal foundation for the AISENTINEL system.

YOLOv11 introduces a comprehensively redesigned backbone network and optimized feature pyramid structures that enable superior feature extraction and contextual awareness [63], [64]. This directly tackles the core problem identified in studies using YOLOv8 and other predecessors, which struggled with the nuanced visual context of a classroom. For instance, while the YOLOv8+ECA model achieved 82.71% accuracy and noted an inability to detect head tilting or phone use under the table [74], YOLOv11's advanced hybrid attention mechanisms allow it to focus on semantically rich regions, significantly improving the detection of small, obscured, or subtle actions like a concealed cellphone or a furtive glance [64], [66].

Furthermore, YOLOv11's architectural refinements translate into tangible performance gains that are critical for a real-time, edge-based system. Where earlier studies using models like YOLOv3 achieved accuracies of 88.03% and explicitly recommended adopting more advanced architectures [75], YOLOv11 has demonstrated a path forward. In controlled experiments, YOLOv11 achieved a state-of-the-art mAP@0.5 of 0.991 across multiple behavior classes while maintaining real-time performance of 30 FPS [6], thereby offering the high-precision and low-latency detection required to make automated proctoring truly reliable.

Finally, YOLOv11 provides enhanced generalization and robustness against the highly variable conditions of a live examination hall, such as fluctuating lighting and complex backgrounds with frequent occlusions [65]. This capability is essential for overcoming the "visibility bias" noted in high-accuracy studies that were likely trained on clearly visible behaviors [76]. By leveraging YOLOv11's improved sensitivity to motion and context, the proposed system aims to close the reliability gap, enabling robust recognition of the very cheating behaviors—quick gestures, concealed notes, and coordinated actions—that have consistently eluded previous systems.

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2.4. Theory Based

It is important to contextualize relevant theories to this study in order to visualize how each of its components interact with each other. This section discusses the theoretical foundations that guide the design and interpretation of our system.

2.4.1. Behavior Recognition Theory

Behavior Recognition Theory focuses on identifying human actions by analyzing patterns in movement and posture. In examinations, it helps distinguish normal student behavior from suspicious actions—such as head tilting, passing objects, or hiding hands—that may indicate cheating. This theory supports automated systems in recognizing deviations from expected exam behavior.

2.4.1.1. Panopticon Theory

The Panopticon Theory, first conceptualized by philosopher Jeremy Bentham and later expanded by Michel Foucault, describes a social mechanism of control through constant surveillance. The central idea is that individuals modify their behavior when they are aware—or even merely believe—that they are being watched, regardless of whether surveillance is continuous or intermittent [59]. In modern applications, this theory extends beyond physical prison architecture and into the realm of digital surveillance, where technology such as AI-based monitoring systems creates a “digital panopticon” [58]. In the context of academic settings, AI-driven proctoring systems mirror this concept by establishing an environment where students are aware of continuous monitoring during examinations. This awareness aims to deter dishonest actions by creating a psychological sense of being observed, thereby encouraging compliance with rules and fostering academic integrity. However, it also raises ethical concerns regarding privacy, autonomy, and the psychological impact of pervasive surveillance [68][59].

2.4.1.2. Cognitive Load Theory

Cognitive Load Theory (CLT), developed by John Sweller, explains how the human brain processes and retains information by considering the limitations of working memory. It identifies three types of cognitive load: intrinsic load, related to the complexity of the material; extraneous load, caused by unnecessary distractions; and germane load, which supports learning through schema construction [60]. Effective instructional design seeks to minimize extraneous load while optimizing germane load to enhance learning efficiency [61]. Research highlights that when individuals experience high cognitive load, their ability to multitask or conceal deceptive actions is significantly reduced [62]. In the context of cheating detection, this theory provides insight into why students under surveillance may exhibit observable behavioral cues—such as fidgeting, excessive head movement, or irregular eye contact—because the cognitive effort required to cheat while appearing natural strains their working memory. Thus, CLT supports the premise that AI-based detection systems, like the one proposed in this study, can effectively identify cheating behaviors by recognizing these subtle stress-induced indicators [60][61][62].

2.4.2. Real-Time Video Processing Theory

Advances in technology and the availability of data from sensors and CCTV have made it possible to identify routine human behaviors and detect anomalies for surveillance purposes. These developments have improved the efficiency and effectiveness of monitoring systems, enabling quick responses to potential threats. Techniques such as Human Action Recognition (HAR), including methods like Histogram of Oriented Gradients (HOG), allow for classification of objects and activities, supporting applications in security, healthcare, sports, elderly care, and human-computer interaction. The accuracy of such systems is influenced by factors including lighting, background, crowded scenes, camera perspective, and activity complexity. Automated analysis also plays a key role in detecting unusual items or behaviors—such as unauthorized objects or rare, unexpected actions—and supports tasks like crowd modeling, tracking, and interpreting collective behavior to help identify risks and anomalies [79].

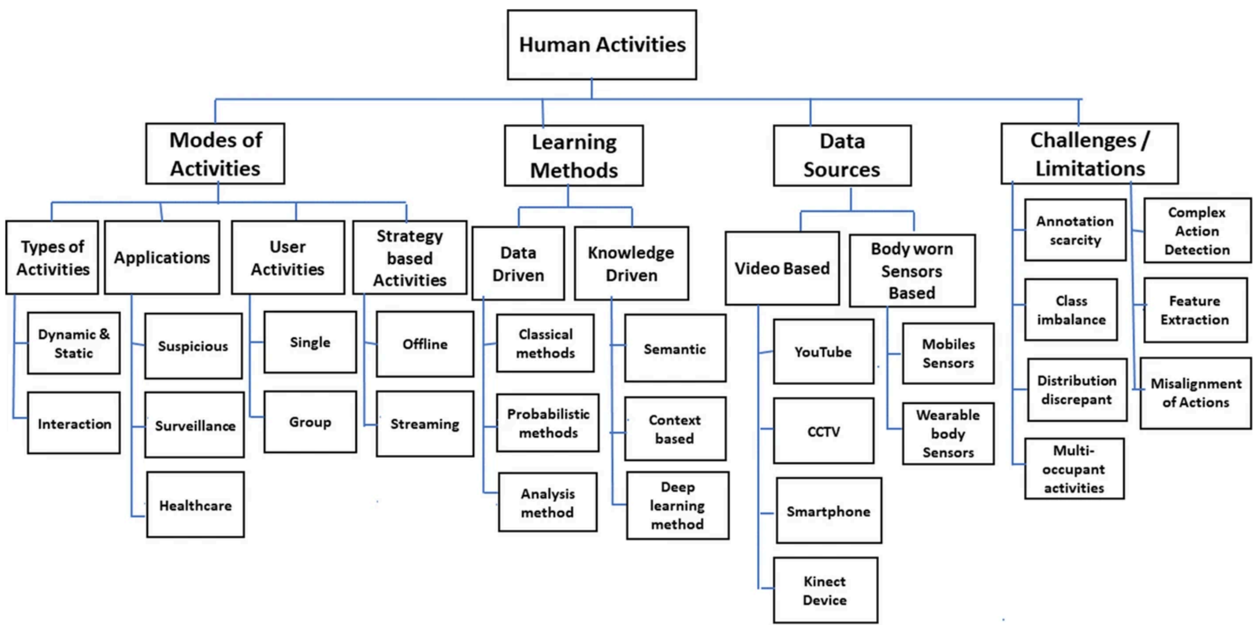

Figure 1. Exploring the HAR Taxonomy: A Multidisciplinary Framework for Classifying Human Activities. Adopted from Bukht et. al [79].

Figure 1 illustrates the overall taxonomy of Human Activity Recognition (HAR) literature. HAR studies human actions using techniques such as machine learning and sensor analysis to enable intelligent monitoring and assistance. Activities are classified as static (e.g., sitting, standing), dynamic (e.g., walking, running), or interactive, and applications span healthcare, surveillance, and detection of suspicious behaviors. Data sources include video- and sensor-based inputs from CCTV, smartphones, Kinect, YouTube, and social media, with video-based data generally requiring more processing power. Existing studies face challenges in areas such as data collection, preprocessing, feature extraction, hardware, complex activity detection, and activity misalignment, which together define the current landscape of HAR research [79].

2.4.3. Object Detection Theory

2.4.3.1. YOLOv11 Real-Time Object Detection

You Only Look Once version 11 (YOLOv11) represents the latest advancement in real-time object detection algorithms, designed to achieve a balance of high detection accuracy and low latency [63]. Building upon the strengths of its predecessors, YOLOv11 introduces enhancements such as improved backbone networks, dynamic anchor-free detection, and optimized attention mechanisms that significantly improve performance in detecting small or partially obscured objects [64][66]. Its architecture supports faster frame rates and higher mean Average Precision (mAP), making it well-suited for applications requiring real-time processing on edge devices [63][64]. For this study, YOLOv11 is selected due to its ability to capture subtle and dynamic cheating behaviors—such as passing notes or abnormal head movements—in real-time and across multiple camera angles. Its improved robustness under variable lighting and complex backgrounds makes it ideal for monitoring in controlled classroom environments where occlusion and movement variability are common [64][65][66]. This technology provides the computational foundation for the system's surveillance using two cameras, ensuring that every area of the examination room is continuously monitored with high precision.

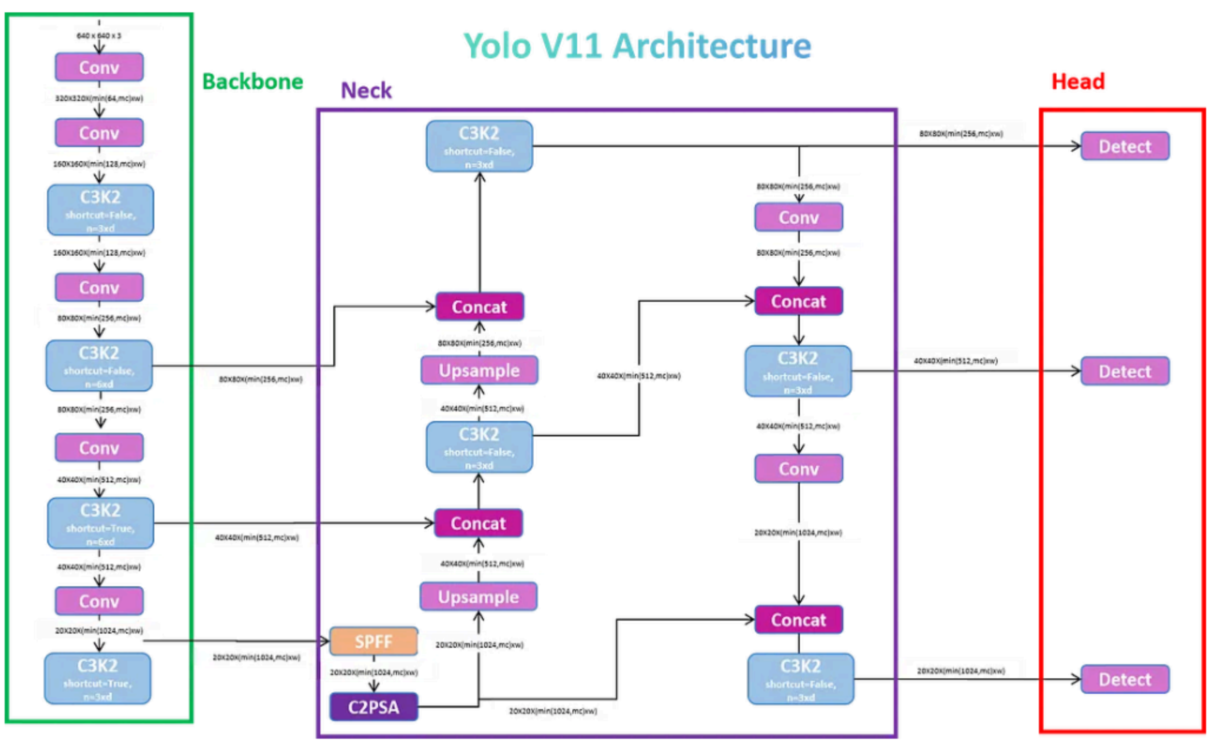

Figure 2. YOLOv11 Model Architecture. Adopted from N. Rao [64]

The YOLOv11 model architecture, as shown in the figure, follows a three-part modular design consisting of the Backbone, Neck, and Head, each performing a distinct role in the object detection process [66]. The Backbone is responsible for extracting features from the input image using multiple convolutional (Conv) and C3K2 blocks. These layers progressively reduce the spatial resolution while increasing the depth of the feature maps, allowing the model to capture both low-level features such as edges and textures, and high-level representations like object structures. The Neck then aggregates and refines these extracted features through modules such as the Spatial Pyramid Pooling Fast (SPPF) and C2PSA, which enable multi-scale feature fusion. Through upsampling and concatenation, the neck integrates information from different resolutions, ensuring accurate detection of small, medium, and large objects while enhancing the robustness of the feature maps by blending global context with fine local details. Finally, the Head is where the actual object detection takes place. It applies detection layers that predict bounding boxes, class probabilities, and object confidence scores across multiple scales. Notably, YOLOv11 employs an anchor-free detection mechanism, simplifying the detection process and improving both accuracy and speed, particularly when identifying small or irregularly shaped objects. With this improved design, YOLOv11 achieves real-time object detection with enhanced precision and efficiency, making it highly suitable for applications such as automated surveillance, and other AI-driven detection systems [64].

2.4.4. Computer Vision Theory

Computer vision has advanced rapidly in recent years, providing tools to interpret and understand visual information without relying on accompanying textual descriptions. With the growth of the Internet and Web-based image sharing, large collections of visual data are now widely accessible, making manual indexing impractical and labor-intensive. Unlike text, which can be directly processed for retrieval, images require extraction and interpretation of visual features alongside high-level conceptual understanding. These capabilities enable applications in image recognition, surveillance, object detection, and human activity analysis, forming the foundation for intelligent visual systems.

2.4.4.1. Color

Color is a key visual attribute that conveys information about objects beyond aesthetics. It aids daily activities such as interpreting traffic signals or identifying teams in sports, and is closely related to the chromatic properties of images. Human color perception involves physical, neurophysiological, and psychological factors. While color distributions are often used for image retrieval due to their robustness under changes in lighting, viewpoint, and scale, recorded color can still vary with surface orientation, illumination, and camera perspective [80].

From a physical perspective, color perception arises from the spectral energy distribution of light reaching the retina, expressed as a function of wavelength E(λ) in the visible range (380–780 nm):

$$E(\lambda) = S(\lambda)R(\lambda)$$

Equation 1. Spectral energy distribution.

where S(λ) represents the spectral distribution of the light source, and R(λ) represents the spectral reflectance of the object. The human visual system perceives differences in E(λ) through three types of cone photoreceptors, sensitive to long, medium, and short wavelengths. The spectral response for each cone type to colored light C(λ) is given by:

$$\alpha i(C) = \int_{\lambda min}^{\lambda max} Si(\lambda)C(\lambda)d(\lambda) \; i = 1, 2, 3$$

Equation 2. Spectral Response.

This formulation links the physical properties of light and surface reflectance to the signals processed by the human visual system [80].

2.4.4.2. Texture

Texture refers to repeated patterns or variations in brightness within an image and is a key visual attribute [80]. It is characterized by image patch size, the number of distinguishable primitives, and their spatial relationships. Texture features, such as granularity, directionality, and repetitiveness, are used in content-based image retrieval, either alone or combined with color and shape. Feature extraction methods include statistical approaches (e.g., co-occurrence matrices), spatial frequency techniques, and multiscale methods like wavelets. Texture analysis supports both similarity-based retrieval and image annotation, with segmentation often critical for accurate feature extraction.

2.4.4.3. Shape

Shape describes the structure of objects within an image and is a fundamental visual attribute [80]. Computational definitions rely on low-level attributes such as boundaries, contours, and spatial arrangements, while humans perceive shape at a high level. Shape similarity can be measured using global descriptors like invariant moments or by modeling deformations through methods such as active contours (snakes) or canonical prototypes. Preliminary segmentation and spatial modeling are often required to handle multiple objects, enabling applications in object recognition and content-based retrieval.

2.4.5. Pose Estimation Theory

Object pose estimation is a central problem in computer vision, supporting applications such as augmented reality, robotics, and scene understanding. Recent advances in deep learning have replaced earlier handcrafted feature-based methods due to their superior accuracy and robustness. Despite this progress, modern models still face challenges, including heavy reliance on annotated datasets, large model sizes, limited robustness to difficult conditions, and reduced generalization to unseen objects [81].

2.4.5.1. Two-Dimensional Pose Estimation

Two-dimensional pose estimation (2D PE) aims to detect and localize key points on the human body, such as the head, shoulders, and knees, within images or videos, providing the 2D coordinates of each joint to analyze body posture and structure. Early approaches relied on probabilistic models and manually designed features, which were computationally intensive and offered limited accuracy. The introduction of deep learning has significantly advanced 2D PE, improving both efficiency and robustness. This section focuses on deep learning-based methods for estimating the poses of single and multiple persons in images and video sequences [82].

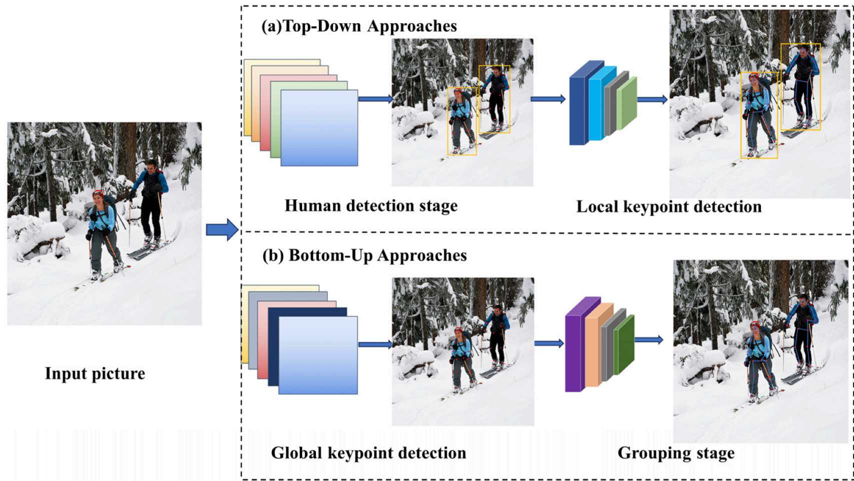

Figure 3. Overview of 2D multi-person PE diagram. (a) Top-down approach; (b) bottom-up approach.

2.4.5.1.1 Top-Down Approach of Two-Dimensional Multi-Person Pose Estimation

Top-down pose estimation methods begin by identifying each individual in an image before predicting the keypoints within the detected bounding boxes [82]. As illustrated in Figure 3a, the process typically starts with person detection, followed by a series of refinement steps that progressively narrow the focus from the entire human region down to precise joint locations. This family of methods usually separates detection and keypoint prediction into two stages, allowing improvements in either component to enhance overall accuracy. Recent developments summarized by [82] involve refining heatmaps, improving spatial feature aggregation, integrating multi-scale features, and enhancing semantic and structural understanding of human body configurations. These enhancements mainly focus on correcting keypoint predictions, enriching feature representation, and improving localization precision across different human poses and scales.

2.4.5.1.2. Bottom-Up Approach for 2D Multi-Person Pose Estimation

Unlike top-down methods, bottom-up approaches detect all keypoints in the entire image first and then group them to construct each human pose [82]. As shown in Figure 3b, this approach merges detection and grouping into a unified process. According to [82], modern bottom-up techniques rely on heatmap-based keypoint detection, spatial configuration cues, and visual characteristics to associate keypoints with the correct person. Some methods integrate graph-based representations, while others use statistical relationships or multi-scale features to achieve more reliable grouping. These strategies help address common challenges such as grouping errors, scale variations, and ambiguous keypoint assignments, ultimately improving efficiency and robustness in multi-person scenes.

2.4.5.1.3. Two-Dimensional Pose Estimation in Videos

Video-based 2D pose estimation introduces additional complexity due to motion, temporal variation, blurring, and potential frame loss [82]. However, using temporal information across consecutive frames can significantly improve prediction stability. As described in [82], several approaches incorporate temporal modeling—such as recurrent networks, temporal refinement modules, or feature propagation—to maintain consistency and reduce errors throughout a video sequence. These methods leverage frame-to-frame relationships to produce more stable pose predictions, even in cases of sparse annotations, non-contiguous frames, or challenging visual conditions. Figure 4 (if present in your source) generally illustrates this concept by showing how pose detection evolves over time or how temporal modules refine predictions across frames.

2.4.6. Real-Time Video Processing Theory

Video data supports a wide range of analytical operations once subjects are detected in a scene, enabling systems to estimate attributes, recognize human poses, identify individuals, and detect motion across frames. Among these capabilities, Human Action Recognition (HAR) is especially relevant, as it interprets human activities directly from video sequences and is widely used to monitor behaviors such as sitting, walking, bending, or falling. HAR is particularly important in environments that require continuous awareness, including injury detection during sports, elderly and childcare, students' classroom behavior analysis, student–teacher classroom action recognition, and surveillance, where understanding interactions and activity patterns helps reveal meaningful behavioral cues and potential anomalies [83].

2.4.7. Edge Computing Theory

Edge computing offers significant advantages for real-time pose estimation because data can be processed directly at or near the source, avoiding the latency and bandwidth limitations commonly associated with cloud-based processing. By handling computation locally, edge systems minimize the need for large data transfers and enable faster, more reliable analysis—especially important for continuous video-based tasks like detecting human poses or behaviors. While cloud computing is better suited for large-scale centralized processing, it introduces higher network pressure, making it less ideal for low-latency applications. In contrast, edge computing supports rapid, small-scale intelligent analysis, providing timely responses with reduced delay and lighter bandwidth demands [84].

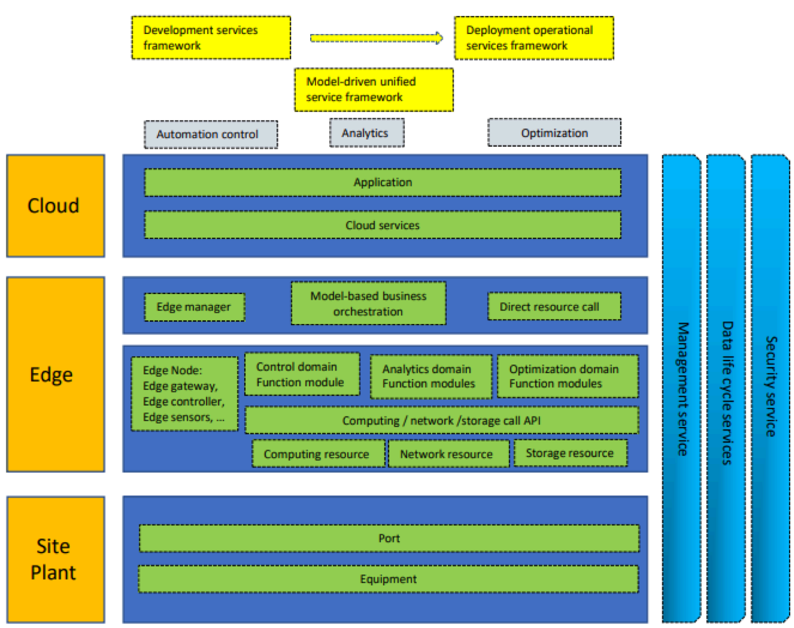

Figure 4. Edge computing reference architecture.

The reference architecture for edge computing is structured as a distributed, federated network that extends cloud capabilities toward the edge by inserting processing devices between end terminals and the cloud. It is generally organized into three layers. The terminal layer includes all end devices connected to the edge network—such as smartphones, sensors, cameras, and smart vehicles—which function as both data producers and consumers. Positioned between these terminals and the cloud is the edge layer, composed of intermediate edge nodes like routers, gateways, access points, switches, and base stations that provide localized computation and communication. Finally, the cloud computing layer contains the most powerful servers and storage systems responsible for large-scale data processing, analytics, and decision support. Through this layered structure, edge computing enables real-time analysis at the network's periphery while reserving more complex tasks for the cloud, creating an efficient and balanced processing pipeline [84].

2.5. Conceptual Framework

Input	Process	Output
• Camera 1 • Camera 2	• Model training • Object detection • Pose estimation	• Real-time alert • Log event • Behavior classification • Evidence clip

Figure 5. Conceptual Framework

The system adopts a straightforward Input–Process–Output logic. On the input side, three hardware elements work in unison to monitor the examination environment: two GSOU T16 Full HD Web Camera units provide comprehensive multi-angle visual coverage of the examination room, while the Raspberry Pi 5 coupled with a Raspberry Pi AI HAT+ 26 TOPS serves as the edge computing backbone for real-time processing.

During processing, the system implements a streamlined computer vision pipeline. The multi-camera video feed undergoes real-time frame processing and is analyzed by a YOLOv11 model optimized for the Edge TPU, which is specifically trained to detect four key cheating behaviors: using mobile phones, consulting cheat sheets, hands under table, tilting heads for unauthorized viewing, and passing papers between students. Crucially, this detection process operationalizes the principles of Cognitive Load Theory (CLT). The system is designed to identify the observable behavioral cues, such as unnatural postures, or fumbling with concealed objects, that manifest when a student's cognitive load is heightened by the simultaneous tasks of test-taking and attempting to deceive the proctor. By focusing on these extraneous load-induced indicators, the system can distinguish between normal exam behavior and the strained, often inefficient movements associated with cheating.

The detection process follows a precise decision tree: when the model identifies suspicious activity with sufficient confidence, the system immediately classifies the behavior type and triggers the output sequence. For each confirmed cheating incident, the system generates a real-time alert for invigilators, records a short evidence video clip, and creates a detailed log event containing the timestamp, specific behavior classification, and originating camera ID. Simultaneously, the behavior classification and evidence are made available through the web interface. When no cheating is detected, the system continues monitoring without intervention, ensuring efficient resource usage. Through this integrated IPO cycle, the framework provides automated, real-time exam proctoring that balances comprehensive surveillance with privacy-conscious operation by recording only during confirmed incidents, thereby supporting academic integrity while minimizing unnecessary data collection.

This Conceptual Framework demonstrates how AISENTINEL transforms raw visual data into reliable, evidence-based outputs that promote fairness, integrity, and transparency in examinations. The system not only aids human invigilators but also supports institutional policies on academic honesty through the combined principles of surveillance deterrence and behavioral recognition. By grounding its operation in Panopticon and Cognitive Load theories, the framework ensures that technological design and ethical principles are harmoniously integrated, fulfilling the study's objectives to develop, implement, and evaluate a real-time cheating detection system deployable on an edge-device platform.

Chapter III
METHODOLOGY

This chapter outlines the research methods and procedures used to create and assess the AISENTINEL system. It describes the experimental and developmental approach, following the Waterfall Model to guide the sequential process of system design, data collection, model training, and deployment on a Raspberry Pi 5 with a Raspberry Pi AI HAT+ 26 TOPS. The procedures for evaluating the system's accuracy and reliability in a controlled examination environment are also specified herein.

3.1 Research Design

The study utilizes the Waterfall Model as its research and developmental framework. This model offers a linear and structured sequence of phases including planning, system design, implementation, testing, and evaluation. This sequential approach ensures systematic progression through the project lifecycle while minimizing errors through rigorous phase completion requirements. Each phase must be fully completed and documented before proceeding to the next stage, which promotes accuracy in implementation, maintains documentation integrity, and ensures complete traceability of all design decisions. The model’s clarity and structured control make it particularly suitable for experimental developmental research that involves both hardware integration and software deployment requiring disciplined sequential progression.

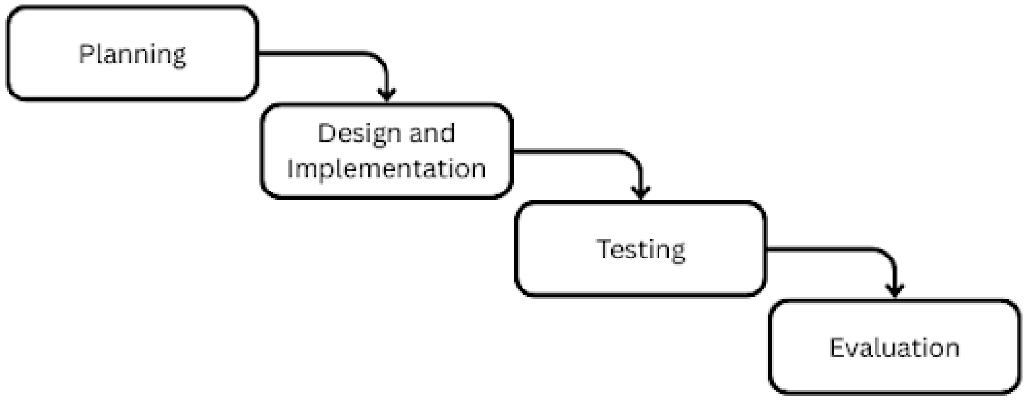

Figure 6. The Waterfall Model. Adapted from

3.2 Research Environment

This study will be conducted in a controlled environment at the College of Engineering, University of Southeastern Philippines, Davao City. The research will utilize a specially configured testing space that simulates examination conditions while maintaining strict experimental controls.

3.2.1 Simulation Control and Experimental Setup

To ensure the validity and consistency of the data, the following controls will be implemented:

- Standardized Layout: The classroom will be arranged in a uniform grid pattern. Desks will be spaced at least 1 meter apart (center-to-center), adhering to post-pandemic guidelines. This spacing is critical to minimize occlusions and ensure each student remains within the camera's field of view with minimal obstruction.

- Lighting and Environmental Control: All testing sessions will be conducted during consistent daytime hours. A combination of stable artificial overhead lighting and controlled natural light from windows will be used to maintain uniform illumination across the room, minimizing shadows and variations in video quality that could affect detection accuracy.
- Pre-defined Cheating Scenarios: A script of cheating behaviors with precise timestamps and participant assignments will be prepared and rehearsed (e.g., "At the 10-minute mark, Student A will use a cellphone under the desk," "At the 20-minute mark, Students B and C will pass a note"). This ensures a balanced dataset with known ground truth, which is essential for accurate system evaluation and metric calculation (Precision, Recall, F1-Score).
- Participant Briefing: All participants will receive a standardized briefing outlining the simulation's purpose, the general types of behaviors they will be asked to perform (both normal exam-taking and pre-scripted suspicious actions), and the session's duration. This ensures all participants understand their role and the experimental context.

3.2.2 Hardware Configuration and Spatial Setup

The physical parameters of the monitoring environment are defined as follows to ensure consistency, reproducibility, and optimal system performance.

- Room Dimensions: The simulation will be conducted in a standard classroom measuring 7 meters in length and 9 meters in width, with a ceiling height of approximately 3 meters.
- Seating Capacity and Arrangement: The testing area will accommodate a maximum of 20 student stations, arranged in a 4x5 grid. Each station consists of a single desk and chair, spaced 1 meter apart as defined in section 3.2.1.
- Camera Specifications and Placement:
    - Camera Model: Two GSOU T16 Full HD Web Cameras will be used.
    - Resolution & Frame Rate: All video feeds will be captured at 1080p (1920x1080) resolution and 30 frames per second.
    - Camera 1 (Front/Wide-Angle): Centered on the front wall, mounted at a height of 2.5 meters above the floor. Tilted downward at a 15-degree angle.
    - Camera 2 (Back/Detailed-View): Centered on the rear wall, mounted at a height of 2.5 meters above the floor. Tilted downward at a 15-degree angle.
    - Field of View (FOV): The positioning of both cameras will be calibrated to ensure their combined FOV covers all 20 student stations completely.

3.2.3. Safety and Ethical Protocols

The safety, privacy, and psychological well-being of all participants are paramount. The following protocols will be strictly enforced:

- Informed Consent: All participants will be provided with a detailed informed consent form. This form will explicitly explain the study's purpose, the nature of the video recording, the data storage and encryption procedures, their right to withdraw at any time without penalty, and the measures taken to protect their anonymity in any published results.
- Data Security: All recorded video evidence, including short event clips, will be stored locally on an encrypted solid-state drive accessible only to the primary researchers. All data, including backups, will be permanently deleted and securely wiped upon the completion of the study and its final thesis defense.
- Psychological Safety: The simulation will be explicitly framed as a test of the system's capability, not an evaluation of the participants' performance or acting skills. A debriefing session will be held immediately after the simulation to address any questions or concerns and to reassure participants about the data handling and anonymization procedures.
- Physical Safety: The research area will be kept clear of tripping hazards. All electrical equipment, including wiring for the cameras,

Raspberry Pi devices, and the Raspberry Pi AI HAT+ 26 TOPS, will be securely installed, managed, and insulated to prevent accidents.

3.3 Research Method

The study employs an experimental and developmental research methodology to design, implement, and evaluate an automated cheating detection system during classroom examinations. This method emphasizes the creation of a functional prototype that integrates hardware and software components, including Raspberry Pi 5, GSOU T16 Full HD Web Cameras, and the YOLOv11 object detection algorithm.

The developmental aspect of the research focuses on constructing the system architecture, integrating image capture, processing, and output functions, and establishing a web-based monitoring platform for data logging. The experimental aspect involves testing the system in a controlled classroom environment, where various scenarios of normal and suspicious student behaviors are simulated.

By evaluating detection accuracy, precision-recall, processing latency, false-positive rate, reliability, and real-time monitoring capability, the study assesses the system's effectiveness in addressing academic dishonesty. This approach allows the researchers to determine the strengths, limitations, and potential applications of the proposed system in educational settings, thereby providing a foundation for future enhancements.

3.4 Sources of Data

This study utilized primary data obtained through experimental testing and simulation methods. A custom dataset was created specifically for training and validating the YOLOv11 cheating detection algorithm to address the unique context of Philippine classroom examinations.

The primary data collection was conducted using two GSOU T16 Full HD Web Cameras, which captured synchronized video footage during simulated examination scenarios. The cameras were configured to record at 1080p resolution and 30 frames per second, generating approximately 72,000 total frames across two 20-minute video recordings.

From this extensive footage, a curated dataset was constructed by selectively extracting approximately 4,000 key frames that contained clear instances of the target cheating behaviors. This frame selection strategy focused on identifying the most representative moments for each cheating category, ensuring training efficiency and model effectiveness rather than annotating all available frames.

The selected frames captured various cheating behaviors including passing papers, head tilting, hands under table, using cellphone, and using cheat sheets. Each frame was meticulously annotated using bounding boxes to identify and label the specific cheating actions in YOLO format. This process ensured high-quality training data for the YOLOv11 model to accurately recognize and classify the target behaviors.

During system validation, the curated dataset of 4,000 annotated images was divided into training, validation, and testing subsets. A standard split of 70% for training, 10% for validation, and 20% for testing was employed. The training set was used to fit the model, the validation set for hyperparameter tuning and early stopping during training, and the held-out test set provided a final, unbiased evaluation of the model's performance.

The data collection was conducted under controlled lighting conditions in a simulated classroom environment at the College of Information and Computing building, University of Southeastern Philippines. Consistent camera positioning and angles were maintained to ensure data quality. All participants provided informed consent, and ethical guidelines were strictly followed throughout the data-gathering process, including privacy protection measures and secure data storage protocols.

3.5 Research Instruments and Tools

Raspberry Pi 5

The Raspberry Pi 5 serves as the primary processing unit of the system. It facilitates data acquisition, executes the YOLOv11 object detection algorithm, and manages real-time processing of captured video streams.

GSOU T16 Full HD Web Camera

The GSOU T16 Full HD Web Camera is the main device for capturing image and video data during classroom examinations. With its 1080p resolution, and reliable autofocus, it ensures clear and accurate video recording for monitoring student activities.

YOLOv11 Algorithm

YOLOv11 functions as the detection tool for identifying suspicious behaviors in real time. It processes captured frames to recognize actions such as mobile phone use, unusual head movements, and other indicators of potential cheating.

Web-Based Monitoring Platform (Google Firebase)

The Firebase-powered monitoring platform acts as the data storage and retrieval system. All detected violations are logged in real time, enabling authorized personnel to access and review incident reports through any internet-enabled device.

Accuracy Evaluation

This section evaluates the overall performance and accuracy of the developed cheating detection system. The assessment compares the system's detections with the invigilator's actual observations to determine how effectively it identifies instances of cheating under real examination conditions. Various test cases were conducted, each representing different behaviors such as cellphone use, paper passing, head tilting, and handling of cheat sheets. The outcomes, summarized in Table 2, indicate whether cheating was observed and correctly detected by the system. Additionally, key performance metrics—including Precision, Recall, mAP@0.5, and Inference Time—were analyzed, as shown in Table 3, to provide a quantitative measure of the model's detection accuracy, reliability, and processing efficiency during operation.

Table 2. Test Result in Cheating Detection

Case #	Cheating Detection			
	Type of Behavior	**Invigilator Observation (Cheating occured?Yes /No)**	**System Detection (Cheating detected?Ye s/No)**	**Description (success/fail)**
1.				
2.				
3.				
4.				
5.				
6.				
7.				
8.				
9.				
10.				

Table 2. Test Result in Cheating Detection

Table 3. The Performance Metrics for YOLOv11n Object Detection

Metrics	***Final Value***
Precision	
Recall	
mAP@0.5	
Inference Time	

Table 3. The Performance Metrics for YOLOv11n Object Detection

3.6 Sampling Technique

The study employs a convenience sampling technique, as participants are selected based on their availability and willingness to take part in the simulation. A small group of students will be gathered in a controlled classroom environment to replicate examination conditions. During the simulation, some participants will answer normally, while others will intentionally perform suspicious actions such as head turning, passing unauthorized materials, hands under table, or attempting to use mobile phones.

This sampling approach allows the researchers to easily access participants while creating realistic classroom scenarios. Conducting the study in a controlled environment ensures consistent conditions for testing, such as lighting, seating arrangements, and camera placement, thereby enabling a reliable assessment of the system's detection capabilities.

3.7 Operational Definitions and Temporal Thresholds

To ensure the AISENTINEL system distinguishes genuine cheating behaviors from normal student movements, specific operational definitions and temporal thresholds were established. These parameters define the minimum sustained duration a behavior must be detected before being classified as a cheating event. The thresholds were derived from preliminary trials and principles in behavioral analysis to minimize false positives.

Table 4. Cheating Behavior Classification Criteria

Behavior	Operational Definition	Temporal Threshold	Rationale
Head Tilting / Looking Away	Sustained deviation of the head from a forward-facing position, inferred from the bounding box trajectory and aspect ratio.	3 seconds	Filters out brief, natural glances and distinguishes intentional observation of a neighbor's work.
Hands Under Table	The bounding box for one or both hands is consistently detected in the lower region of the frame (below the desk plane) and absent from the upper body area.	2 seconds	Excludes momentary actions like picking up a dropped pen or adjusting seating position.
Using Cellphone / Cheat Sheet	A prohibited object (cellphone, paper sheet) is detected within the student's personal desk area.		The presence of the prohibited object itself is a violation.
Passing Papers	A hand holding a paper is detected moving outside one student's bounding box region.		The act of a paper being transferred between students is an immediate

			violation. The system flags this based on the object's position relative to student bounding boxes in a single frame or across two consecutive frames.

Table 4. Cheating Behavior Classification Criteria

Multi-frame Verification and Multi-camera Validation

All detections are subject to a multi-frame verification logic. A potential event must be detected in a consecutive sequence of frames that corresponds to the temporal threshold (e.g., 90 frames at 30 FPS for a 3-second threshold) before an alert is triggered. This temporal consistency strategy is a well-established practice for reducing transient false detections in video analytics [77], [78].

Furthermore, the two-camera configuration provides spatial validation. For an event to be confirmed, the behavior should be observable from at least one other camera angle, ensuring it is not an artifact of a single camera's perspective or a momentary occlusion. This multi-angle verification significantly enhances the system's reliability before a cheating event is officially logged.

3.8 Procedure of the Study

The study follows the Waterfall model, which is a sequential process for developing a specific project. The researchers utilize the model by having the following steps:

Step 1: Planning

This phase focuses on establishing the foundation of the study through careful scheduling and preparation. The researchers outline the sequence of activities, create a timeline, and identify the required resources for the project. Essential components such as the Raspberry Pi 5, GSOU T16 Full HD Web Cameras, data ports, and connecting wires will be procured either through online platforms or physical electronic shops. Proper supervision will be considered in selecting the working environment to ensure safety and accuracy during the research process. To support the technical aspects of the project, consultations with programmers and subject-matter experts will also be arranged. Furthermore, reference materials and preparatory documents will be gathered to guide the study and align it with its objectives.

Step 2: Implementation

This stage discusses the processes of designing and implementing the input, processing, and output sections. Also, this stage discusses the system architecture.

A. Input Section

a. Image Data Collection

GSOU T16 Full HD Web Camera - a webcam equipped with fast autofocus and a wide-angle lens option, delivering clear video output suitable for various recording and monitoring tasks. It supports smooth 1080p video capture, providing consistent and reliable performance for classroom and examination settings.

Figure 7. GSOU T16 Full HD Web Camera

B. Processing Section

a. Raspberry Pi 5 Microprocessor - It is a single-board, low-cost, high-performance microcontroller. It primarily facilitates the overall processing of the system.

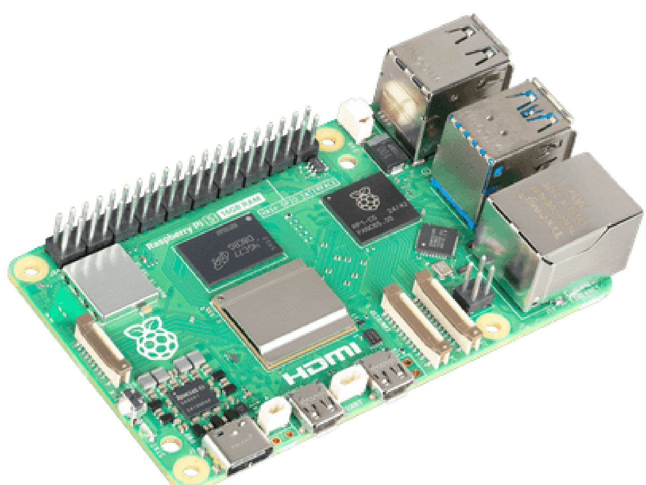

Figure 8. Raspberry Pi 5 Microprocessor

b. YOLOv11 - You Only Look Once version 11 is a deep learning algorithm commonly used for real-time object detection and recognition. In this study, it is applied to monitor students during examinations by detecting suspicious activities such as the use of mobile phones or unusual head movements that may indicate cheating behavior.

c. Raspberry Pi AI HAT+ 26 TOPS - features a Hailo-8 neural network inference accelerator capable of 26 tera-operations per second, supporting large AI networks, faster inference, and simultaneous execution of multiple networks. It connects to the Raspberry Pi 5 via PCIe, which automatically detects the NPU and leverages it for AI tasks.

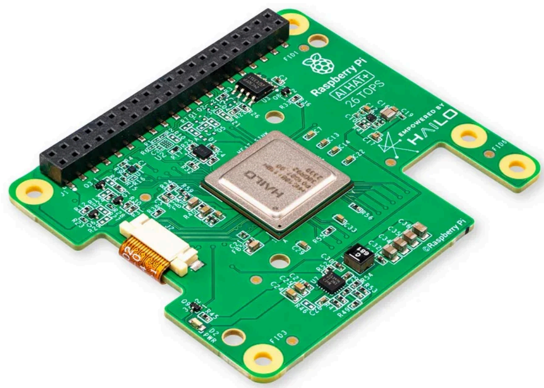

Figure 9. Raspberry Pi AI HAT+ 26 TOPS

C. Output Section

a. Website - The study utilizes a Google Firebase–based website as the platform for data logging and information retrieval. All detected violations and suspicious activities are recorded in real time and stored in the Firebase database. The website serves as the monitoring dashboard, allowing authorized personnel to access, review, and manage incident reports efficiently through any internet-enabled device.

D. System Architecture

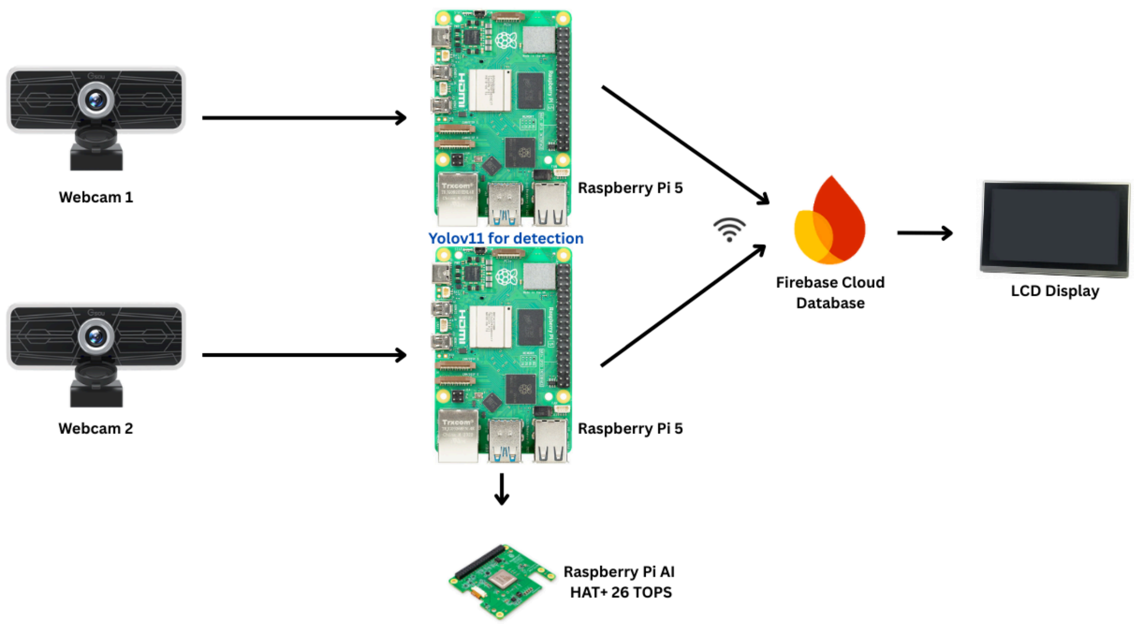

Figure 10. Overall System Architecture of the Study

E. Output System

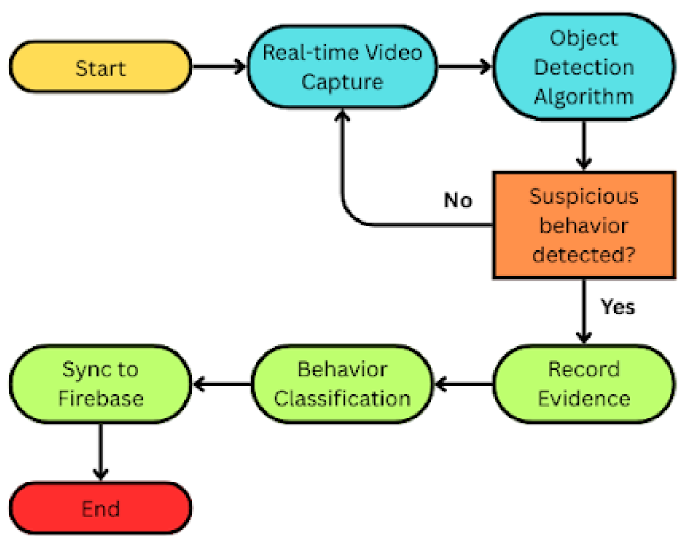

Figure 11. Flowchart of Output System

Step 3: Testing

The system will be tested to evaluate its accuracy and reliability in detecting cheating behaviors during a simulated classroom examination. Testing will be conducted during daytime hours in a controlled classroom environment, ensuring proper lighting and seating arrangements similar to actual examination conditions. The two GSOU T16 Full HD Web Cameras will be mounted above the classroom at angles that provide clear views of the students.

The testing will involve a small group of participants who will simulate different examination scenarios. Some students will answer normally, while others will intentionally perform suspicious behaviors such as head turning, passing items, hands under table, using cheat sheets, and attempting to use a mobile phone. The system's outputs will be logged and compared with actual observed behaviors to determine detection accuracy.

Step 4: Evaluation

The system will be evaluated to measure its overall performance in detecting cheating behaviors. The evaluation will focus on the accuracy of detecting suspicious activities such as head turning, use of mobile phones, and other prohibited actions during examinations. Data gathered from the testing phase will be organized into successful and unsuccessful detections, which will then be represented using a confusion matrix. Key performance metrics, such as accuracy, precision, recall, and F1-score, will be derived through statistical treatment to determine the effectiveness and reliability of the system.

3.9 Statistical Treatment

The data analysis for this research will focus on evaluating the performance of the proposed cheating detection system using a confusion matrix and its associated metrics of accuracy, precision, recall, and F1 score. Together, these statistical measures will provide a comprehensive assessment of how effectively the system identifies and classifies suspicious student behaviors during examinations.

For cheating detection, a confusion matrix will be utilized to assess and summarize the performance of the classification algorithm, applicable to both binary and multiclass scenarios. This matrix will provide insights into how accurately the system distinguishes between normal student behavior and potential cheating activities. As shown in Figure 8, the confusion matrix will consist of four key metrics: true positives, true negatives, false positives, and false negatives that serve as the foundation for calculating the system's performance indicators.

3.9.1 Confusion Matrix

The confusion matrix will be utilized specifically in the assessment of the overall performance of the system. In the case of this study, the results will be in binary classification, where the system determines whether cheating behavior is present or not. The confusion matrix, shown below, will consist of four primary characteristics that serve as the classifier's measuring metrics:

1. True Positive (TP): the number of cheating instances correctly detected
2. True Negative (TN): the number of non-cheating instances correctly identified
3. False Positive (FP): the number of non-cheating instances incorrectly classified as cheating (Type I error)
4. False Negative (FN): the number of cheating instances incorrectly classified as non-cheating (Type II error)

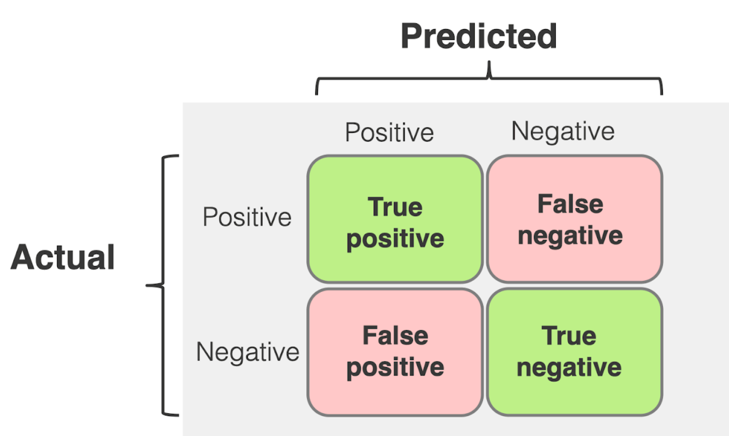

Figure 12. Confusion Matrix

In this study, the model is designed as a multi-class classification system, categorizing five labels: normal behavior, head tilting, using mobile phone, passing items, hands under table, and using cheat sheet. Figure 12 illustrates the generated confusion matrix from the developed model for detecting potential cheating behaviors during classroom examinations.

	Normal Behavior	Head Tilting	Using Mobile Phone	Passing Items	Using Cheat Sheet	Hands Under Table	Total (Predicted)
Normal Behavior							
Head Tilting							
Using Mobile Phone							
Passing Items							
Using Cheat Sheet							
Hands Under Table							
Total (Predicted)							

Figure 13. Modified Confusion Matrix

By examining the confusion matrix, key performance metrics for the YOLOv11 object detection model can be derived. These metrics evaluate the system's effectiveness in identifying various cheating behaviors. Precision measures the system's reliability when it triggers an alert. A high precision indicates that when the system detects a cheating behavior (e.g., "using cellphone"), it is highly likely to be correct, thereby minimizing false alarms for invigilators. The formula for calculating precision is as follows:

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

Equation 3. Precision

Recall (also known as Sensitivity) measures the system's ability to find all actual instances of cheating. A high recall indicates that the system misses very few cheating events, making it a thorough monitor. The formula for recall is:

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

Equation 4. Recall

The F1-Score is a single, balanced metric that harmonizes the trade-off between precision and recall. It is the harmonic mean of the two and is especially useful for providing a holistic view of the model's performance across different cheating behavior classes, particularly when the class distribution is imbalanced. The formula for the F1 score is as follows:

$$F1\ Score = \frac{2TP}{2TP + FP + FN}$$

Equation 5. F1 Score

Accuracy, while a general indicator, evaluates the overall correctness of all the system's predictions by considering both correct detections and incorrect ones across all classes. However, for object detection in imbalanced scenarios, it can be misleading if used alone. The formula for accuracy is:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Equation 6. Accuracy

Mean Average Precision (mAP) is the primary metric for evaluating object detection models like YOLO. It summarizes the precision-recall curve and is calculated as the average precision across all classes and over multiple Intersection over Union (IoU) thresholds, providing a comprehensive measure of both localization and classification accuracy.

References

[1] B. Ives and A.-M. Cazan, “Did the COVID-19 pandemic lead to an increase in academic misconduct in higher education?,” Higher Education, 2023. doi: 10.1007/s10734-023-00996-z

[2] X. Liu and N. Alias, “An empirical survey on prevalence and demographic differences in academic dishonesty among undergraduates from four public universities in China,” *Higher Education Evaluation and Development*, vol. 17, no. 1, pp. 52–65, 2023.

[3] Anitha, P., & Sundaram, S. (2021): Prevalence, Types and Reasons for Academic Dishonesty among College Students. Journal of Studies in Social Sciences and Humanities, 7(1), 1-14.

[4] M. G. W. Aguilar, “Academic Dishonesty in the Philippines: The Case of 21st Century Learners and Teachers,” International Journal of Multidisciplinary: Applied Business and Education Research, vol. 9, no. 1, pp. 44–55, 2021.

[5] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, “You Only Look Once: Unified, Real-Time Object Detection,” in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Las Vegas, NV, USA, Jun. 2016, pp. 779-788.

[6] Kim, S. J., & Kim, M. J. (2025). *Cheating detection in examinations using YOLOv11: A comprehensive real-time object detection framework for enhancing academic integrity. Research Square.* https://doi.org/10.21203/rs.3.rs-6376844/v1

[7] G. Holi, P. K. L., M. A., S. R., and S. Harshitha, “Intelligent Offline Exam Monitoring System for Identifying Suspicious Behavior of the Student,” Int. J. Comput. Appl., vol. 187, no. 15, pp. 27–33, Jun. 2025. [Online].

Available:
https://ijcaonline.org/archives/volume187/number15/holi-2025-ijca-925125.pdf

[8] T. Liu, X. Zhang, Y. Wang, and M. Chen, "AI Proctoring for Offline Examinations with 2-Longitudinal-3D Convolutional Networks," Comput. Biol. Med., vol. 146, p. 105506, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2666920X22000704

[9] M. S. Adhantoro, R. F. Santoso, and P. H. Prasetyo, "Development of an Exam Cheating Detection System Based on Facial Recognition Using Deep Learning," J. Appl. Technol. Innov., vol. 10, no. 14, pp. 1–9, 2025. [Online]. Available: https://www.jatit.org/volumes/Vol103No14/23Vol103No14.pdf

[10] S. Kaddoura, "Towards Effective and Efficient Exam Systems Using Deep Learning Models for Real-Time Cheating Detection," Comput. Biol. Med., vol. 145, p. 105473, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2667305322000904

[11] Raspberry Pi, "Introducing the Raspberry Pi AI HAT+ with up to 26 TOPS," Raspberry Pi News, Oct. 24, 2024.

[12] F. von Hippel, J. P. C. M. van der Meer, and E. A. P. Poortinga, "Privacy as Contextual Integrity in Online Proctoring Systems in Higher Education: A Scoping Review," *arXiv preprint arXiv:2310.18792*, 2023. [Online]. Available: https://arxiv.org/abs/2310.18792

[13] D. Lichauco et al., “Academic dishonesty in online classes: Investigating self-reports using McCabe’s Academic Integrity Survey,” Asia Pacific Journal of Education, Arts and Sciences, vol. 10, no. 1, pp. 1–9, 2023.

[14] DepEd, “Promoting Academic Honesty (DM-OUCI-2021-395),” Department of Education Philippines, 2021.

[15] CHED, “Policies, Standards, and Guidelines on Academic Integrity,” Commission on Higher Education Philippines, 2022.

[16] R. V. Amorado and R. N. Vilchez, *Pedagogy of Fraud: Cheating Practices in Online Classes*, C & E Publishing, Inc., 2024.

[17] B. C. G. Lisao, “Academic integrity in peril: Teachers’ challenges and strategies in upholding academic honesty in the face of generative artificial intelligence,” *Eur. J. Educ. Stud.*, 2025. [Online]. Available: https://oapub.org/edu/index.php/ejes/article/view/6162

[18] U. C. Agwi, M. E. Irhebhude, and F. N. Ogwueleka, “Video surveillance in examination monitoring,” *Security & Privacy*, vol. 4, no. 2, e144, 2020. DOI: 10.1002/spy2.144.

[19] IRJMETS, “AI-Powered Cheating Detection in Offline Examinations Using YOLOv8 and Pose Detection,” International Research Journal of Modern Engineering & Technology and Science, vol. 5, no. 3, 2025.

[20] *The Independent*, “Rise in number of students cheating, using phones or being disruptive in exams,” Dec. 14, 2023. [Online]. Available: https://www.independent.co.uk/news/uk/england-geoff-barton-schools-association-of-school-and-college-leaders-b2464355.html

[21] PhilNews, “PNPA cadets expelled after cheating in exam,” July 6, 2023. [Online]. Available: https://philnews.ph/2023/07/06/2-pnpa-cadets-expelled-after-caught-cheating-during-exam/

[22] M. Lichauco *et al.*, "Online classes in the Philippines," *J. Social Humanities Educ.*, 2023. [Online]. Available: https://goodwoodpub.com/index.php/jshe/article/view/1500

[23] R. Castaño, "Online and blended learning in the Philippines," *South Asian J. Sci. Technol.*, 2020. [Online]. Available: https://www.sajst.org/online/index.php/sajst/article/view/266

[24] J. Cleto, "Prevalence and forms of academic dishonesty," *Int. J. Adv. Appl. Sci.*, vol. 11, no. 7, pp. 1–8, 2024. [Online]. Available: https://www.science-gate.com/IJAAS/2024/V11I7/1021833ijaas202407009.html

[25] L. Lisao, "Integrity risks with generative AI," *Eur. J. Educ. Stud.*, vol. 12, no. 1, pp. 1–12, 2025. [Online]. Available: https://oapub.org/edu/index.php/ejes/article/view/6162

[26] Pragyanam School, "Importance of exams in schools," *Pragyanam School Blog*, n.d. [Online]. Available: https://www.pragyanam.school/blog/the-importance-of-exams-in-schools/

[27] Global Indian International School, "Why exams matter for fairness," *GIIS Blog*, n.d. [Online]. Available: https://globalindianschool.org/jp/tokyo/blog-details/what-is-the-importance-of-exams-for-students-in-schools/

[28] IEEE, "Early approaches on activity recognition in education," in *Proc. Chinese Control Conf. (ChiCC)*, 2014, pp. 6896–6901. [Online]. Available: https://sci-hub.se/10.1109/ChiCC.2014.6896205

[29] Academia.edu, "Automatic unusual activities recognition using deep learning in academia," *Academia Papers*, 2021. [Online]. Available: https://www.academia.edu/62051796/Automatic_Unusual_Activities_Recognition_Using_Deep_Learning_in_Academia

[30] IEEE, "Deep learning for activity recognition," in *Proc. IEEE Int. Conf. Electronics, Computing and Communication Technologies (CONECCT)*, 2020, pp. 1–6. [Online]. Available: https://sci-hub.se/10.1109/CONECCT50063.2020.9198691

[31] ResearchGate, “Identification of classroom sheet exam cheating trials using a deep learning approach,” *Res. Artic.*, 2024. [Online]. Available: https://www.researchgate.net/publication/380855271_Identification_Of_Classroom_Sheet_Exam_Cheating_Trials_Using_a_Deep_Learning_Approach

[32] Academia.edu, “Automated cheating detection based on video surveillance in the examination classes,” *Academia Papers*, 2022. [Online]. Available: https://www.academia.edu/83240647/Automated_Cheating_Detection_based_on_Video_Surveillance_in_the_Examination_Classesb

[33] MDPI Sensors, “Advanced YOLO-based cheating detection,” *Sensors*, vol. 23, no. 8, p. 4149, 2023. [Online]. Available: https://www.mdpi.com/1424-8220/23/8/4149

[34] ResearchGate, “Real-time detection of examination malpractices using convolutional neural networks and video surveillance: A systematic review with meta-analysis,” *Res. Artic.*, 2024. [Online]. Available: https://www.researchgate.net/publication/391727591_Real-Time_Detection_of_Examination_Malpractices_Using_Convolutional_Neural_Networks_and_Video_Surveillance_A_Systematic_Review_with_Meta-Analysis

[37] MDPI Data, “Open dataset on cheating detection,” *Data*, vol. 7, no. 9, p. 122, 2022. [Online]. Available: https://www.mdpi.com/2306-5729/7/9/122

[38] W. Wijk, J. Peters, and K. Müller, “Deep learning inference on edge,” in *Proc. Int. Conf. Artificial Neural Networks (ICANN)*, 2023, pp. 350–362. [Online]. Available: https://link.springer.com/chapter/10.1007/978-3-031-77731-8_25

[39] MDPI Data, “Cheating detection dataset: Annotation challenges,” *Data*, vol. 7, no. 9, p. 122, 2022. [Online]. Available: https://www.mdpi.com/2306-5729/7/9/122

[40] Tertiary Education Quality and Standards Agency (TEQSA), “Strategies for using online invigilated exams,” *Policy Guidance*, 2022. [Online]. Available: https://www.teqsa.gov.au/sites/default/files/2022-10/strategies-for-using-online-invigilated-exams.pdf

[41] *Journal of Interprofessional Education & Practice (JIPE)*, "Preparing invigilators for active, in-person exam delivery," *JIPE*, vol. 28, pp. 81–89, 2022. [Online]. Available: https://jipe.ca/index.php/jipe/article/view/81

[42] PubMed Central (PMC), "Implementation of an intelligent exam supervision system," *Res. Artic.*, 2022. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC9459801/

[43] PubMed Central (PMC), "No chit chat! A warning from a physical versus virtual invigilator," *Res. Artic.*, 2022. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC9355029/

[44] T. Liu, X. Zhang, Y. Wang, and M. Chen, "AI proctoring for offline examinations with 2-longitudinal-3D convolutional networks," *Comput. Biol. Med.*, vol. 146, p. 105506, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2666920X22000704

[45] Scientific Research Publishing (SCIRP), "Academic integrity and exam invigilation/proctoring risks," *Open Access J.*, 2024. [Online]. Available: https://www.scirp.org/journal/paperinformation?paperid=136422

[46] PubMed Central (PMC), "A systematic review of cheating in online and blended contexts," *Systematic Rev.*, 2022. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC8898996/

[47] Quality and Qualifications Ireland (QQI), "E-proctoring in theory and practice: A review," *Policy Report*, 2021. [Online]. Available: https://www.qqi.ie/sites/default/files/2021-12/e-proctoring-in-theory-and-practice-a-review.pdf

[48] UK Government, "Remote invigilation within vocational and technical qualifications," *Policy Guidance*, 2023. [Online]. Available: https://www.gov.uk/government/publications/remote-invigilation-in-vocational-and-technical-qualifications/remote-invigilation-within-vocational-and-technical-qualifications

[49] *Open Praxis*, "An evaluation of online proctoring tools," *Open Praxis*, vol. 12, no. 4, pp. 455–466, 2020. [Online]. Available: https://openpraxis.org/articles/10.5944/openpraxis.12.4.1113

[50] *iJOE*, "AI-based proctoring limitations," 2023. Available: https://online-journals.org/index.php/i-joe/article/view/39583

[51] *Mendeley Data*, "Dataset for cheating detection," 2022. Available: https://data.mendeley.com/datasets/39xs8th543/1

[52] *PMC*, "Study on AI-based proctoring challenges," 2022. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC9358372/

[53] *ScienceDirect*, "Advances in cheating detection using deep learning," 2024. Available: https://www.sciencedirect.com/science/article/abs/pii/S0262885624001586

[54] *LabelYourData*, "YOLO object detection overview," 2023. Available: https://labelyourdata.com/articles/yolo-object-detection

[55] *MDPI Applied Sciences*, "AI-based examination monitoring," vol. 14, no. 10, p. 4048, 2024. Available: https://www.mdpi.com/2076-3417/14/10/4048

[56] *MDPI Applied Sciences*, "Deep learning for cheating detection," vol. 13, no. 19, p. 11114, 2023. Available: https://www.mdpi.com/2076-3417/13/19/11114

[57] *MDPI Sensors*, "YOLO-based cheating detection in classrooms," vol. 23, no. 8, p. 4149, 2023. Available: https://www.mdpi.com/1424-8220/23/8/4149

[58] *Springer*, "Panopticon and surveillance in education," 2025. Available: https://link.springer.com/article/10.1007/s11023-025-09723-2

[59] *EBSCO*, "Historical overview of the Panopticon," n.d. Available: https://www.ebsco.com/research-starters/history/panopticon

[60] *ScienceDirect*, "Cognitive load theory in psychology," n.d. Available: https://www.sciencedirect.com/topics/psychology/cognitive-load-theory

[61] *SET Foundation*, "Importance of cognitive load theory in education," n.d. Available: https://set.et-foundation.co.uk/resources/the-importance-of-cognitive-load-theory

[62] *Medical College of Wisconsin*, “Cognitive load theory faculty guide,” n.d. Available: https://www.mcw.edu/-/media/MCW/Education/Academic-Affairs/OEI/Faculty-Quick-Guides/Cognitive-Load-Theory.pdf

[63] *arXiv*, “YOLOv11: Next-level object detection,” 2024. Available: https://arxiv.org/html/2410.17725v1

[64] N. Rao, “YOLOv11 explained: Enhanced speed and accuracy,” *Medium*, 2024. Available: https://medium.com/@nikhil-rao-20/yolov11-explained-next-level-object-detection-with-enhanced-speed-and-accuracy-2dbe2d376f71

[65] *Nature*, “YOLOv11 applications in science,” 2025. Available: https://www.nature.com/articles/s41598-025-96314-x

[66] *ScienceDirect*, “YOLOv11 in applied detection research,” 2024. Available: https://www.sciencedirect.com/science/article/pii/S2590123024017341

[67] Y. Zuo, S. S. Chai, and K. L. Goh, “Cheating Detection in Examinations Using Improved YOLOv8 with Attention Mechanism,” *Journal of Computer Science and System Programming*, vol. 14, no. 2, pp. 1668–1680, 2024.

[68] Vázquez, J. J. (2021). Can we stay one step ahead of cheaters? A field experiment on the effects of proctoring. Journal of Behavioral and Experimental Economics.https://www.sciencedirect.com/science/article/abs/pii/S2214804320306960

[69] Henderson, M., & S. A. Y. (2023). The temptation to cheat in online exams: moving beyond the technological fix. International Journal for Educational Integrity. https://link.springer.com/article/10.1007/s40979-023-00143-2

[70] McCarley, J. S., & Yamani, Y. (2021). Psychometric curves reveal three mechanisms of vigilance decrement. Psychological Science. https://journals.sagepub.com/doi/10.1177/09567976211007559

[71] Gyles, S. P., & McCarley, J. S. (2023). Psychometric curves reveal changes in bias, lapse rate, and sensitivity in an online vigilance task. Attention, Perception, & Psychophysics. https://link.springer.com/article/10.3758/s13414-023-02652-1

[72] Holden, O. L., Nelson, J., & Slamet, A. (2021). Academic integrity in online assessment: A research synthesis. Frontiers in Education.https://www.frontiersin.org/articles/10.3389/feduc.2021.639814/full

[73] Lancaster, T., & Clarke, P. A. (2020). Detecting and prosecuting contract cheating with evidence – a 'Doping Test' approach. International Journal for Educational Integrity.https://edintegrity.biomedcentral.com/articles/10.1007/s40979-020-00056-4

[74] Zuo, Y.; Chai, S. S.; Goh, K. L., "Cheating Detection in Examinations Using Improved YOLOv8 with Attention Mechanism," *Journal of Computer Science and System Programming*, 2024. https://thescipub.com/abstract/jcssp.2024.1668.1680 Science Publications

[75] Sharma, A.; Patel, R. K.; Chen, L., "Automatic Cheating Detection in Exam Hall Using YOLOv3 and ShuffleNet," in *Proc. 2023 International Conference on Computer Vision and Pattern Recognition (CVPR)* — I found a PDF version in the International Journal of Novel Research and Development: https://www.ijnrd.org/papers/IJNRD2311094.pdf IJNRD

[76] M. A. Alvi; S. Deng; T. Yamamoto, "A Comparative Study of Deep Transfer Learning Algorithms for Cheating Detection in Exams Based on

Surveillance Camera Recording," IEEE Access, 2023. https://dl.acm.org/doi/10.1145/3626641.3626933

[77] Y. Zuo, S. S. Chai, and K. L. Goh, "Cheating Detection in Examinations Using Improved YOLOv8 with Attention Mechanism," *Journal of Computer Science and System Programming*, vol. 14, no. 2, pp. 1668–1680, 2024. Available: https://thescipub.com/pdf/jcssp.2024.1668.1680.pdf

[78] A. O. A. Moyo, K. T. Kabo-Bola, and C. K. Kandiero, "Advanced AI Examination Monitoring and Security System," in *Proceedings of the 17th International Conference on Computer Vision Theory and Applications (VISAPP 2025)*, ScitePress, 2025. [Online]. Available: https://www.scitepress.org/Papers/2025/136127/136127.pdf