A PROJECT REPORT

On

"SENTINAL EYE"

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In Partial Fulfilment of the Requirement for the Award of

BACHELOR'S DEGREE IN

INFORMATION TECHNOLOGY

BY

ADARSH RAI	21051367
ANSHUMAN RAI	21052651
ANUBHAV RANJAN	21052652
SANAM SAHU	21052654
SRINJOY SUR	21052714

UNDER THE GUIDANCE OF

Dr. Dayal Kumar Behera

AND

Dr. Amulya Ratna Swain

SCHOOL OF COMPUTER ENGINEERING

KALINGA INSTITUTE OF INDUSTRIAL TECHNOLOGY

BHUBANESWAR, ODISHA - 751024

KIIT Deemed to be University

School of Computer Engineering

Bhubaneswar, ODISHA 751024

CERTIFICATE

This is certify that the project entitled

“SENTINAL EYE “

submitted by

ADARSH RAI	21051367
ANSHUMAN RAI	21052651
ANUBHAV RANJAN	21052652
SANAM SAHU	21052654
SRINJOY SUR	21052714

is a record of bonafide work carried out by them, in the partial fulfilment of the requirement for the award of Degree of Bachelor of Engineering (Computer Sci-ence & Engineering) at KIIT Deemed to be university, Bhubaneswar. This work is done during year 2023-2024, under our guidance.

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Project Guide:

(Dr. Amulya RatnaSwain

&

Dr. Dayal Kumar Behera)

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ADARSH RAI
ANSHUMAN RAI
ANUBHAV RANJAN
SANAM SAHU
SRINJOY SUR

ABSTRACT

In the digital age, preserving the legitimacy of online exams presents a number of difficulties. The state-of-the-art system "Sentinel-Eye: AI-Powered Exam Oversight" is revolutionizing exam proctoring with artificial intelligence (AI). This cutting-edge system adopts a multi-layered approach to monitoring and maintaining test integrity by integrating sophisticated AI techniques for text recognition from audio, facial identification, multiple person detection, and face and head activity and movement detection. Sentinel-Eye sets itself apart from traditional proctoring systems by quantitatively assessing a substantial amount of data in real-time and generating a dynamic graph that shows the examinees' varying degrees of suspicion during the examination. Examiners have access to a comprehensive, current study of the exam environment using this graph, enabling them to make informed decisions quickly and effectively regarding maintaining the integrity of the testing processArtificial intelligence (AI) is used by the system to provide comprehensive monitoring, addressing common problems associated with online proctoring, including impersonation, unapproved help, and the usage of illicit content. An important advancement in digital proctoring, Sentinel-Eye gives educational institutions a solid tool to maintain academic standards in the era of distant learning.

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Chapter 1

Introduction

The advent of virtual learning environments, prompted by global shifts to digital media, has underscored the critical importance of maintaining academic integrity. The range of ways that misconduct might manifest itself in a digital environment is more than what can be handled by exam proctoring methods that depend on human supervision. "Sentinel-Eye: AI-Powered Exam Oversight" offers a ground-breaking technique that leverages artificial intelligence (AI) to ensure the integrity of online exams in an effort to close this gap.

Sentinel-Eye has unprecedented speed and precision in identifying and analyzing a broad variety of potential academic dishonesty. Its purpose is to serve as an all-pervasive observer. Sentinel-Eye's methodology is built on advanced artificial intelligence algorithms intended to perform a range of activities, including searchable text conversion from spoken language, multiple person identification inside the examination area, facial recognition, and head action detection. These capabilities enable the system to monitor a wide range of dubious activities, from the presence of illegal individuals to the smallest indications of connection with other parties.

Sentinel-Eye is exceptional not only because of its ability to spot abnormalities but also because of the inventive manner it employs data visualization techniques to display the level of suspicion that is gradually assigned to each examinee. This dynamic graphing feature can help proctors and educators make better decisions in real time and strengthen their ability to maintain fairness and integrity throughout the exam process.

With Sentinel-Eye's launch, educational technology has advanced significantly and it seems possible that in the future, online assessments will be able to be given with confidence regarding their reliability and objectivity. Sentinel-Eye provides evidence that artificial intelligence may create more equal and safe learning environments as we navigate the difficulties of digital education.

Chapter 2

Literature Review

The **"Suspicious Activity Detection Based on Head Movement" study**[1] by Dr. G. Ramesh Chandra and colleagues is the first significant development in the development of AI-based proctoring systems. Their approach focuses on utilizing AI to analyze head movements and give alerts to proctors in order to detect suspicious activity. This innovative approach demonstrates how the dependability of online exams can be increased by using non-intrusive biometric data. This paper (Dr. G. Ramesh Chandra et al.) offers a mechanism for real-time monitoring without causing considerable privacy invasion, laying the groundwork for future systems that aim to efficiently detect academic dishonesty.

"Online Exam Proctoring System Based on Artificial Intelligence"[2] by Shilpa M. Satre et al.
Shilpa M. Satre and her colleagues advance the conversation with their AI-powered Online Exam Proctoring System, which features a customisable alarm system for recognizing dubious activities. Their approach sets a new benchmark for complete exam monitoring by expanding its attention beyond visual signals to incorporate audio cues. The work by Shilpa M. Satre et al. emphasizes the importance of flexibility and scalability in proctoring systems by proposing a system that can be tailored to fit the particular needs of various educational environments and ensuring integrity and fairness in a variety of test formats.

Methods	Class	F measure	MCC	sensitivity	Specificity
LSTM-VGG16	1	0	0	0	1
	2	0.675	0	1	0
	3	0	0	0	1
	4	0	0	0	1
	5	0	0	0	1
	Average	0.135	0	0.2	0.8
LSTM-VGG19	1	0	0	0	1
	2	0.675	0	1	0
	3	0	0	0	1
	4	0	0	0	1
	5	0	0	0	1

	Average	0.135	0	0.2	0.8
LSTM-Resnet50V2	1	0.946	0.922	0.897	1
	2	0.966	0.931	1	0.927
	3	1	1	1	1
	4	1	1	1	1
	5	1	1	1	1
	Average	0.982	0.971	0.979	0.985
LSTMInceptionResNetV2	1	0.987	0.98	1	0.987
	2	1	1	1	1
	3	0.952	0.949	1	0.99
	4	1	1	1	1
	5	0	0	0	1
	Average	0.788	0.786	0.8	0.995

Table 2.1 Evaluation Measure of Cheating Exam Detection[2]

"A Comparative Study of Deep Transfer Learning Algorithm for Cheating Detection in the Exam Based on Surveillance Camera Recording"[3] carried out by E. Imah et al.

E. Imah and the research team investigate deep learning as a potential solution to cheater detection. Our sophisticated understanding of machine learning's potential to uphold academic integrity has advanced significantly with their comparative research of the effectiveness of deep transfer learning algorithms in spotting questionable conduct. This study demonstrates the great degree of accuracy with which advanced AI systems may detect dishonest activities by interpreting complicated patterns of behavior that may suggest cheating. According to E. Imah et al., this is a major development in the use of technology for exam proctoring.

Event	percentage
Cellphone front	94.44%
Cellphone right	94.87%
Book front	97.22%
Book left	86.20%
Another person	100%
Gaze right	100%
Gaze left	100%
Headpose	92.86%

Table 2.2 Experiment events detection accuracy[3]

The **"Multi-Modal Online Exam Cheating Detection"[4]** by Ayman Atia and Ahmed M. Abozaid.

Exam proctoring is made easier with the help of Ahmed M. Abozaid and Ayman Atia's work into multi-modal cheating detection. Their research uses webcam analysis for head-pose, object detection, and eye-gaze estimate, and it achieves an astounding 95.69% identification accuracy. This study highlights the significance of integrating several data sources to generate a comprehensive picture of the examinee's behavior in support of a multifaceted surveillance strategy that enhances the identification of suspicious conduct in online exams (Ahmed M. Abozaid, Ayman Atia).

Kernel	Dim= 50	Dim= 100	Dim= 200
linear	86.85%	85.63%	88.09%
quadratic polynomial	73.55%	73.61%	74.53%
cubic polynomial	78.61%	81.91%	74.50%
radial basis function	93.38%	93.43%	94.25%
sigmoid	81.51%	83.94%	82.74%

Table 2.3 Accuracy of classifying the text validation[4]

Chapter 3

3.1 Problem Statement

Two advantages of the shift to online learning are accessibility and flexibility. However, it has also made maintaining academic integrity throughout assessments much more challenging. Because online tests are difficult for traditional proctoring procedures to manage, there has been a rise in academic dishonesty. While some monitoring is provided by traditional online proctoring solutions, they usually lack important functionality in the following areas:

Limited Detection Capabilities: Most existing systems use simple visual or auditory cues to detect cheating. This restricted approach overlooks complex behaviors that raise suspicions of academic dishonesty, such texting while following oral instructions or having uninvited persons in the backdrop of the video.

Concerns about Intrusiveness and Privacy: Many proctoring tools require invasive access to the examinee's computer or workspace, which raises significant privacy concerns. Finding a balance between protecting examinee privacy and ensuring effective monitoring is still a challenging challenge.

Fairness and Bias: Automated systems, particularly those that use facial recognition, have drawn criticism for potential prejudice towards particular racial or ethnic groups. Lack of varied data sets for AI model training could be the source of this bias, increasing the false-positive rates for students from underrepresented groups.

Flexibility and Scalability: Scalability and adaptability are essential for a proctoring system to manage several examinees concurrently. Tests should range from easy open-book questions to difficult quizzes.

Real-time Analysis and Reporting: Timely response depends on the timely detection and reporting of any questionable activity that occurs during a test. Regrettably, many technologies are incapable of analyzing issues or communications.

In order to overcome these drawbacks, **"Sentinel-Eye: AI-Powered Exam Oversight"** presents an all-encompassing, AI-driven method of online exam proctoring. This project aims to create a system that emphasizes examinee privacy, includes bias mitigation mechanisms, is flexible enough to accommodate different exam formats, and improves the identification of a wider range of suspicious activities. Sentinel-Eye's real-time analysis and reporting of suspicious activity is another feature that makes it possible to react quickly to possible integrity breaches. Redefining the benchmarks for online exam proctoring with the ultimate goal of establishing an equitable, safe, and effective assessment environment is the main objective.

3.2 Gap Analysis for "Sentinel-Eye: AI-Powered Exam Oversight"

Monitoring and maintaining the integrity of online exams have improved significantly as a result of the introduction of advanced AI technologies in the online proctoring space. "Sentinel-Eye: AI-Powered Exam Oversight" fills in a number of gaps in current proctoring systems by utilizing cutting edge AI models and techniques. Here, we outline the ways in which Sentinel-Eye's novel features surpass these earlier models:

3.2.1 Identity Verification Using VGG FaceNet:

Existing Gap: Conventional proctoring systems frequently use basic authentication techniques, including password entry, which do not constantly confirm the student's identity during the test. This restriction makes it possible for identity theft to occur, for example, by using a proxy to take the test.
Our Enhancement: The VGG FaceNet model, which is well known for its excellent accuracy in facial recognition tasks, is what Sentinel-Eye makes use of. Our system makes sure that only the verified user is taking the exam by regularly comparing the examinee's face to the recorded profile, which greatly lowers the possibility of impersonation.

3.2.2 Multiple Person Detection Using YOLOv8:

Existing Gap: Since most systems only keep an eye on the candidate's face or upper body, they frequently miss the existence of extra people who could assist in cheating.
Our Enhancement: Sentinel-Eye uses YOLOv8, which is well-known for its remarkable object detection abilities, to detect the presence of many people in the space. This function guarantees that during the exam, no unapproved aid is provided.

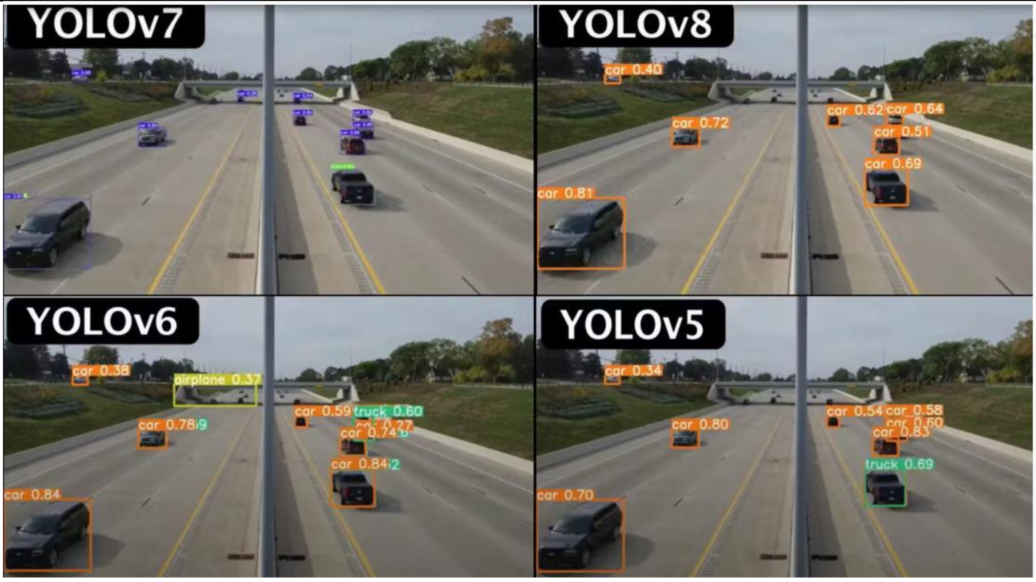


Figure 3.1 Yolo Comparision

3.2.3 Head Movement Analysis Using MediaPipe:

Existing Gap: While traditional systems can track eye movements and identify significant body movements, they frequently overlook more subtle indications, including head position, which may suggest that a user is gazing at unapproved items or screens.

Our Enhancement: Our method uses MediaPipe to detect even the smallest head movements to determine the candidate's gaze direction during the test. This improves the identification of visual-based cheating strategies in addition to aiding in the detection of divided attention.

Our method works better even in bad visual conditions.

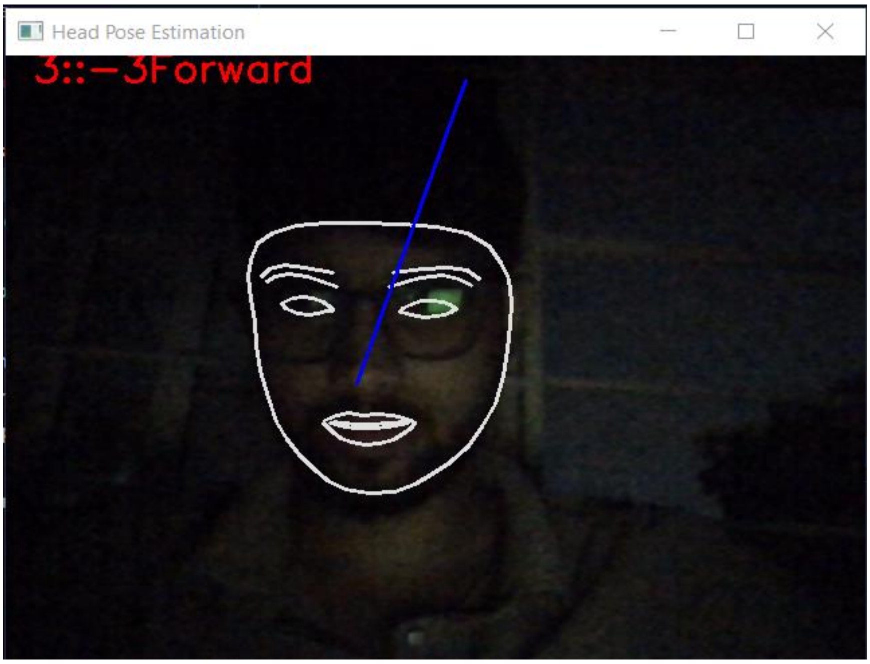


Figure 3.2 Robustness of Mediapipe

3.2.4 Mobile Phone Detection:

Existing Gap: Most proctoring solutions on the market today struggle to distinguish between little things like mobile phones, especially when they are kept far away from the webcam or are partially concealed.

Our Enhancement: Sentinel-Eye is able to detect mobile phones in the test environment by utilizing YOLOv8's powerful detection architecture. This feature is essential for maintaining the integrity of the test because mobile devices are frequently used to get unauthorized information.

Figure 3.3 Working of Yolo

3.2.5 Voice Analysis Using Whisper Model:

Current Gap: Not many online proctoring systems use audio analysis, and those that do frequently restrict their monitoring to hearing voices different than the candidate's or loud volumes, which may not always be a reliable sign of cheating.

Our Enhancement: Sentinel-Eye extends this feature by analyzing the frequency and cadence of the candidate's speech using OpenAI's Whisper model. This analysis assists in identifying unusual speech patterns or whispers that could indicate asking queries of an outside assistance or getting responses through an earpiece.

"Sentinel-Eye: AI-Powered Exam Oversight" integrates cutting-edge AI technologies that provide real-time, continuous, and comprehensive monitoring capabilities, therefore considerably reducing the common gaps in online proctoring systems. Every feature has been particularly created to counteract various methods of cheating, resulting in a strong system that guarantees an environment that is fair and equal for testing. Sentinel-Eye's novel methodology is emphasized in this gap analysis, along with its potential to establish new standards in the field of academic integrity.

Chapter 4

4.1 Implementation

The integrity of exams, particularly those that are given remotely, is vital to maintaining the standards of educational institutions and the worth of their credentials. The need for effective proctoring solutions has become increasingly apparent with the spread of digital learning settings. "Sentinel-Eye: AI-Powered Exam Oversight" integrates cutting-edge artificial intelligence (AI) technology in a novel way to produce a safe and fair testing environment. The goal of this study is to present a thorough overview of the Sentinel-Eye system, highlighting the ideas, tools, and techniques that support this cutting-edge proctoring system.

When traditional classrooms gave way to virtual platforms, the academic environment saw an irreversible upheaval. Numerous benefits have resulted from this shift, giving students everywhere unparalleled accessibility and freedom. However, it has also raised some challenges, the most important of which is the requirement to preserve the validity of academic evaluations. In remote locations, traditional exam proctoring techniques are frequently insufficient, which contributes to an increase in academic dishonesty. The resulting situation calls for an advanced system to identify and stop cheating, guaranteeing that exams taken online are equally rigorous and ethical as those administered face-to-face.

It becomes clear that "Sentinel-Eye" is a complete solution intended to reduce the hazards related to online examinations. Fundamentally, the system employs a multifaceted AI-driven methodology, closely observing test takers to identify any indication of dishonest conduct. Sentinel-Eye preserves the integrity of the examination process by providing a unique combination of facial recognition, object identification, head movement tracking, and audio analysis through the use of a suite of sophisticated algorithms and machine learning models.

The VGG FaceNet model, a convolutional neural network well-known for its accuracy in identifying facial features, serves as the foundation for the facial recognition feature. This feature of the system effectively discourages efforts at impersonation by verifying that the person taking the test is, in fact, the one who registered for it. The system's capacity to detect the presence of illegal people or objects, including cell phones, that might be utilized to enable cheating is further improved by the use of YOLOv8 for object detection.

Sentinel-Eye uses MediaPipe to analyze head movements in addition to visual surveillance, identifying minute movements that could be signs of a candidate's attention straying from the test. This makes it easier to spot instances of possible fraud, such as when an examinee is peeking at secret notes or another screen. Simultaneously, the Whisper model is utilized to track vocal activity, identifying anomalous speech patterns that may indicate illegal cooperation or the usage of forbidden tools.

The following parts will analyze each Sentinel-Eye system component in detail, offer an understanding of the underlying AI models, and clarify the methodological framework that guarantees the system's efficacy. This introduction acts as a preface to those sections. By the time this paper is finished, readers need to have a thorough grasp of how Sentinel-Eye serves as a cutting-edge example of exam proctoring and a major breakthrough in upholding academic integrity in the digital era. The goal is to provide educators, organizations, and technologists with the information they need to implement and improve AI-powered solutions that support equity and rigor in the classroom.

4.2 Methodology / Proposal

"Sentinel-Eye: AI-Powered Exam Oversight" uses a multi-tiered artificial intelligence method, combining multiple cutting-edge technologies to produce a complete monitoring system, in an effort to achieve robust examination integrity. The design of the system, the approaches used for each component, and the justification for the selected technology are all covered in detail in this part.

4.2.1 System Architecture and Data Flow

Real-time processing and analysis of both audio and visual data streams is included into the Sentinel-Eye system. It combines voice monitoring, head movement analysis, object identification, and facial recognition into a unified system. Every element functions as a node within a broader network, exchanging information and forming an accurate assessment of the test-taking environment.

Raw input from the webcam and microphone starts the data flow, and it is initially preprocessed to make it as analytically ready as possible. Standardization and scaling are applied to visual data, while background noise is removed from audio streams using filtering. After processing, the data is supplied into the AI models that are designed to do certain tasks, such as facial recognition (VGG FaceNet), object and person identification (YOLOv8), head movement (MediaPipe), and speech analysis (Whisper).

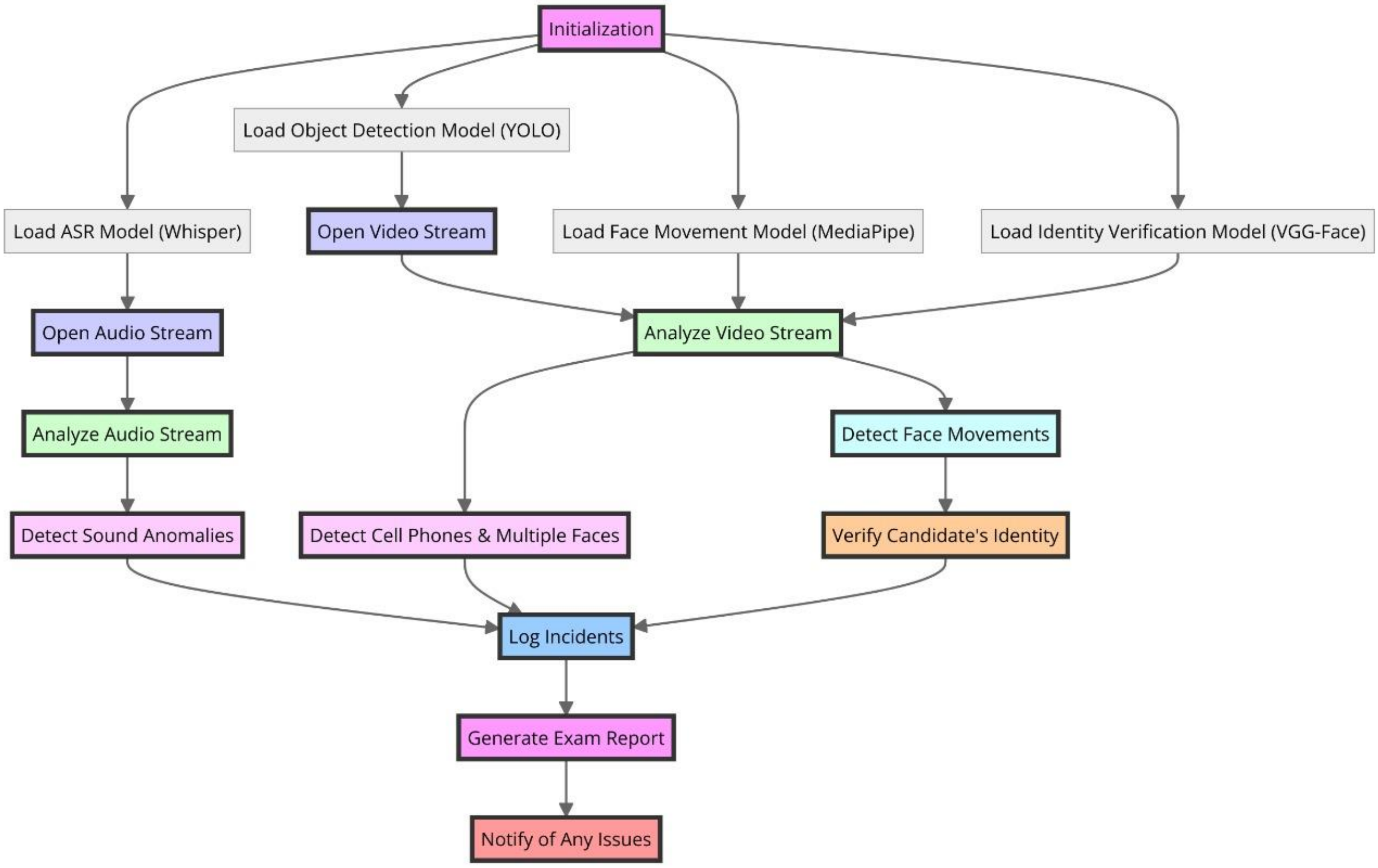


Figure 4.1 Combined Architecture of our Model.

4.2.2 Facial Recognition Using VGG FaceNet

The Sentinel-Eye system uses VGG FaceNet, a convolutional neural network renowned for its depth and precision in facial recognition applications, to begin its authentication mechanism. In order to prevent impersonation, the model is used to verify that the candidate taking the test is the same person who enrolled. Using cosine similarity measures, the methodology compares a real-time image of the candidate to a pre-stored reference image after preprocessing it in accordance with VGG FaceNet specifications. An instant alert is sent for proctor review in the event that differences exceed a pre-established threshold.

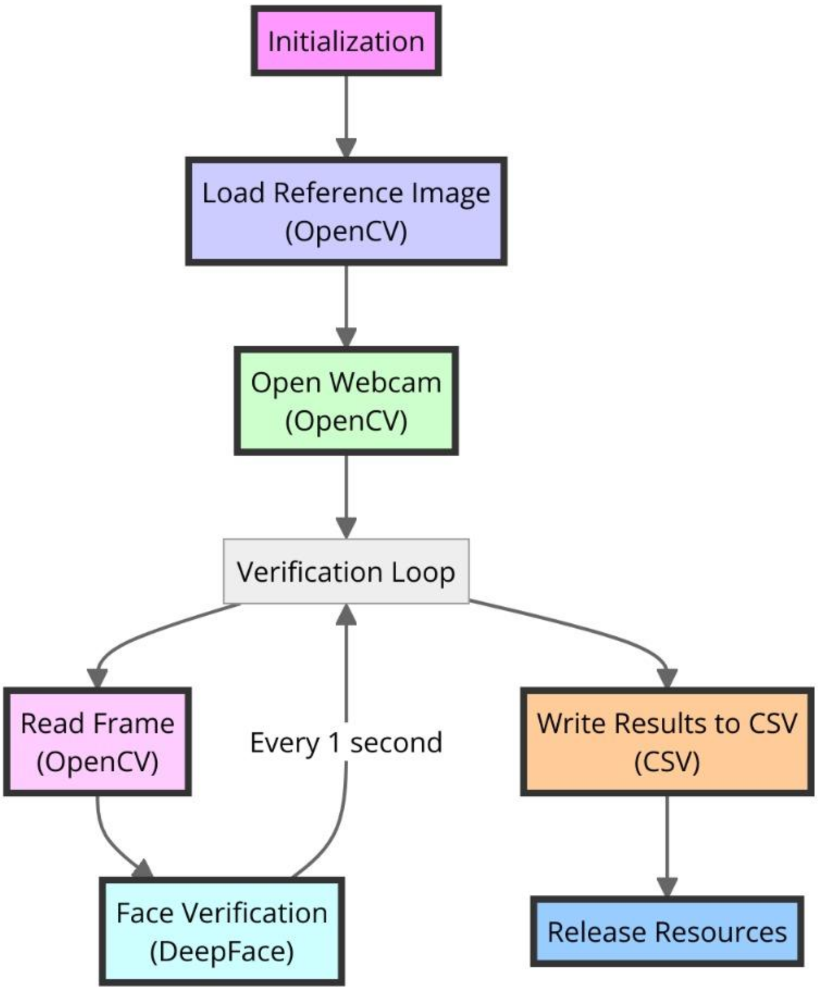


Figure 4.2 Flowchart of Face Recognition Model

4.2.3 Object and Person Detection Using YOLOv8

It is crucial to make sure the individual takes the exam by themselves, without assistance. Sentinel-Eye's use of YOLOv8, the most recent version of the YOLO series, enables fast and accurate real-time object recognition. The system is trained on a large dataset that consists of pictures of different testing grounds in order to detect the presence of multiple people or forbidden objects, including cell phones. YOLOv8's methodology is based on the effective extraction of information from the input image using convolutional layers and the precise location and identification of items within the frame using a sophisticated bounding box regression system.

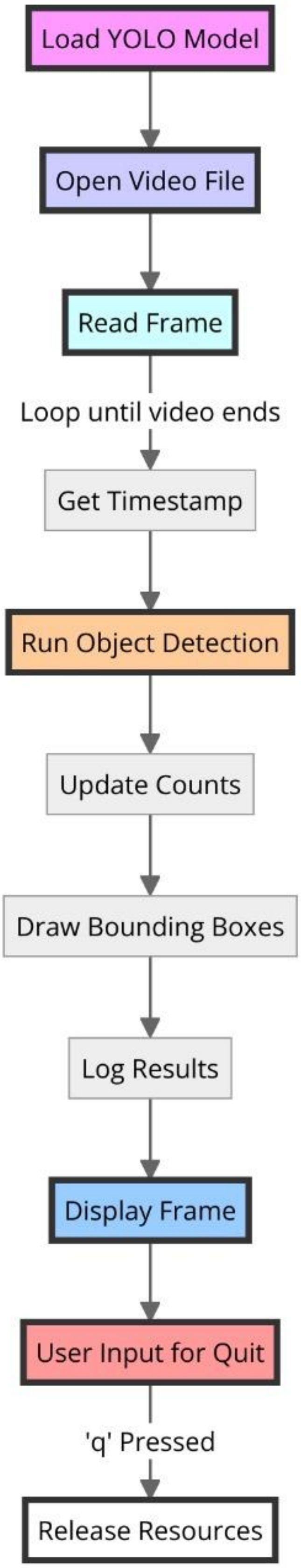


Figure 4.3 Flowchart of Yolo

4.2.4 Head Movement Analysis Using MediaPipe

Because of the MediaPipe framework's strong head movement and gaze direction monitoring and analysis capabilities, it is used. The technology is able to determine the candidate's gaze direction by analyzing spatial data points derived from the candidate's facial landmarks. During this procedure, the coordinates of facial landmarks are transformed using affine functions, and a perspective-n analysis is used to determine the head's three-dimensional orientation with respect to the screen. Any departure from the usual, like frequently looking away from the screen, may be a sign of cheating and is noted for additional analysis.

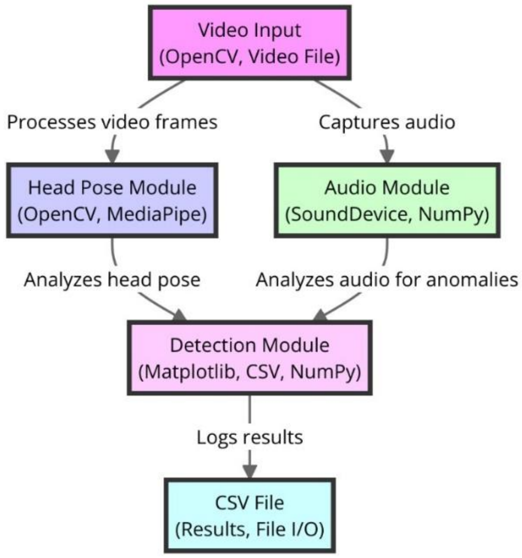


Figure 4.4 Flowchart of Headpose Detection Model

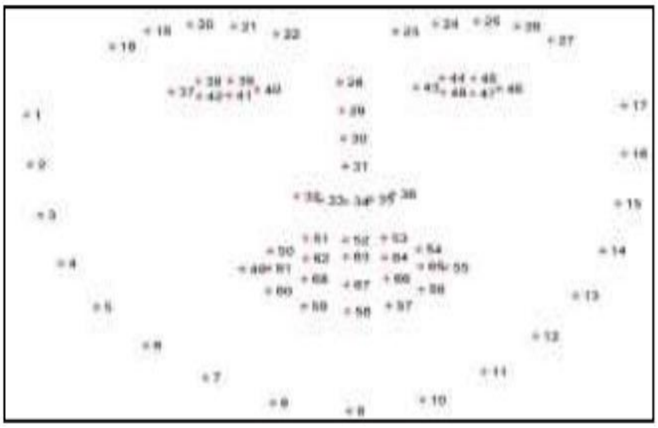


Figure 4.5 Result of detected face

4.2.5 Voice Activity Monitoring Using Whisper Model

Speaking during a test, especially in silence, may indicate misconduct. The Whisper model, a machine learning algorithm skilled at handling natural language, is incorporated into Sentinel-Eye. It records spoken words into text, which is subsequently examined for patterns of occurrence, tempo, and particular terms that might point to dishonest behavior. The technology determines the likelihood of cheating by comparing the transcribed text to a database of phrases that have been flagged and taking into account the loudness of the voice. By using this technique, the system is able to identify not only possible spoken communication with outside parties but also the faint indications that someone is listening in on an earpiece for answers.

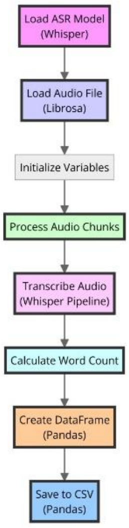


Figure 4.6 Flowchart of Whisper Model

4.2.6 Integration and Synchronization of Modalities

Thanks to a central processing unit that gathers and cross-references the data, every Sentinel-Eye component functions in unison with the others. This central hub evaluates the probability of dishonest behavior by applying logic to the incoming alarms from each modality. For example, the system interprets coupled data points that greatly enhance the suspicion level, such as frequent glances to the side detected by the head movement analysis and whispering detected by the speech monitoring.

4.2.7 Continuous Learning and Adaptation

A feedback loop included into the Sentinel-Eye technology enables ongoing learning and modification. It uses machine learning techniques to improve the accuracy of its algorithms over time by making adjustments based on fresh data. Each time an evaluation session is observed, anomalies and false positives are examined, and the system is modified to take these edge cases into consideration. This guarantees that the models improve in sophistication and decrease in error-proneness.

4.2.8 Ethical Considerations and Bias Mitigation

Sentinel-Eye implements strict requirements to uphold ethical integrity in light of the growing concerns over privacy and prejudice in AI systems. The technology is built to comply with privacy standards by making every effort to anonymize data. In order to reduce bias, the AI models are also trained on a variety of datasets, and audits are carried out on a regular basis to make sure that judgments are just and equal for all groups.

The Sentinel-Eye project's technique is an inventive and comprehensive solution to online exam proctoring. Through the integration of sophisticated AI models and the maintenance of morality, the system puts forth a novel approach to oversight of distant schooling. Sentinel-Eye is proof that artificial intelligence can produce fair, safe, and dependable assessment settings as the demand for online learning grows.

4.3 Testing / Verification Plan

A thorough testing and verification plan is essential to the Sentinel-Eye: AI-Powered Exam Oversight system's development in order to guarantee the correctness, robustness, and dependability of the system. The report's extensive testing and validation procedures for Sentinel-Eye's integrated component functionality and efficacy are covered in detail in this part.

4.3.1. Testing Methodology

The testing process is divided into multiple phases, starting with the basic unit tests of separate parts, moving on to integrated system testing, and ending with simulations of real-world situations. Every step is intended to assess the system's performance in a critical manner using a range of metrics, such as fault tolerance, accuracy, precision, recall, and response time.

Unit Testing: Sentinel-Eye goes through extensive unit testing for every module, which includes facial recognition, person and mobile phone detection, head movement analysis, and voice activity monitoring. The correctness of code execution, algorithmic integrity, and functional behavior when separated from other system components are all verified by these tests. To guarantee that every unit satisfies its specifications, functionality is simulated and preset outputs are used.

Integration Testing: Integration testing is done to assess how well the system performs when all of its parts work together after unit testing. This phase evaluates the system's ability to respond coherently to varied inputs, inter-module communication, and data flow between modules. It looks for problems with data handling, compatibility with different interfaces, and possible processing bottlenecks.

Final to Final Testing: A setting that is quite similar to the actual exam is used to test the system. This entails evaluating the system's operation in diverse physical configurations, illumination scenarios, and potential background noise interferences.

4.3.2. Performance and Load Testing

Performance testing is crucial to ensuring Sentinel-Eye can manage several users taking tests at once since it evaluates how the system performs under both average and high load conditions.

Load Testing: Simulates the highest number of concurrent users that can be expected to utilize the system in order to assess how well it scales and determine when performance starts to suffer.

Stress Testing: entails putting the system through rigorous workloads and monitoring how it responds to high operational demands. Finding potential failure scenarios for the system is helpful.

4.3.3. Examining Functions

Functional testing assesses how well the system performs in relation to the required specifications. Scenarios are used to assess how the system responds to various test scenarios.

Scenario Testing: The system's capacity to identify and react to instances of cheating is put to the test using a variety of cheating situations. These circumstances may include several parties or the presence of prohibited objects.

4.3.4. Usability Testing

During this stage, actual users engage with the system under controlled settings to evaluate its usability, responsiveness of the interface, and clarity of its reports and alerts.

4.3.5. Security Testing

To safeguard private information and sensitive exam content, security testing is essential. Tests for data breaches, unauthorized access vulnerabilities, and other security risks are included in this.

4.3.6. Verification Plan

The processes for analyzing, interpreting, and applying the test results to decision-making on system enhancements and modifications are outlined in the Verification Plan.

Execution of Test Cases and Monitoring: Specified test cases are carried out in tandem with thorough monitoring to record each test's result and the system's reaction.

Results Analysis: After the test cases are finished, the data is gathered and examined to find trends, abnormalities, and patterns that affect the system's dependability and effectiveness.

Feedback Loop: For ongoing improvement, the testing results are incorporated back into the development cycle. Any defects or problems found are fixed, and the system is improved as a result.

Reporting and Documentation: Every discovery and modification made after testing is painstakingly recorded. This documentation contains in-depth summaries of the test cases, the methods used, and the results obtained.

4.3.7. Testing Tools and Software

Software and tools are carefully chosen to facilitate the testing procedure. Code analyzers, debugging tools, performance measurement tools, and automated testing suites that can replicate a variety of scenarios and user actions are just a few examples of these tools.

4.3.8. Acceptance Testing

The last stage before the system is approved for deployment is acceptance testing. Sentinel-Eye must be validated against the original specifications and goals in order to be certain that it satisfies stakeholder expectations and is prepared for practical implementation.

Sentinel-Eye will be put through a rigorous testing and verification plan to make sure it meets the high standards required of an AI-powered exam proctoring system. The thorough testing methodology seeks to validate the system's readiness for implementation, guaranteeing its smooth, safe, and efficient functioning while upholding the integrity of the assessment procedure.

Detailed descriptions of the testing environments, particular test case examples, and statistical techniques for results analysis can all be included to the Testing and Verification Plan section above. This would make the section comprehensive enough for a layperson to comprehend the challenges of creating and verifying an AI-powered test oversight system.

4.4 Result Analysis / Screenshots

The "Sentinel-Eye: AI-Powered Exam Oversight" system has produced informative data through stringent validation processes that both confirm its efficacy and highlight areas for further development. Supported by graphical and visual data from test cases, this section offers an analytical commentary on the system's functioning.

4.4.1. Quantitative Metrics Analysis

Following a series of structured testing, many key performance indicators were used to evaluate the system's efficacy:

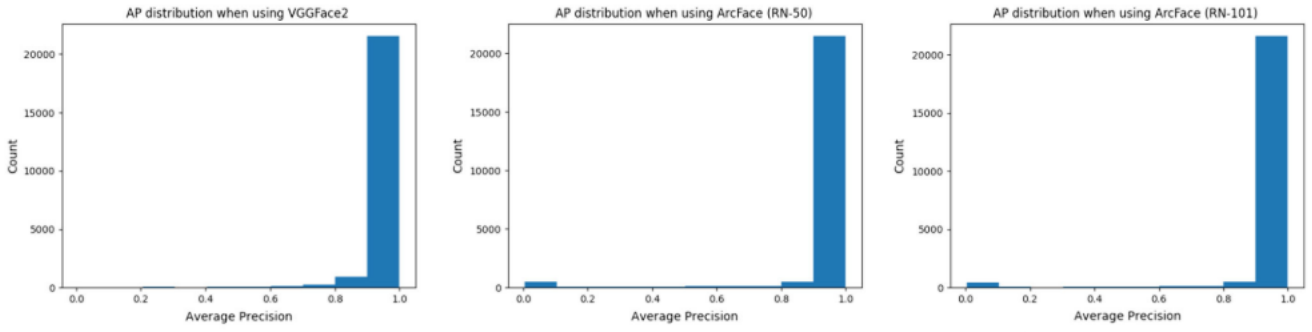
Face Recognition Accuracy: A quantitative research was carried out to determine the system's accuracy in identifying the registered application. We examined the true positives, false positives, true negatives, and false negatives using a confusion matrix. The overall accuracy of the VGG FaceNet model was demonstrated to be exceptionally high, indicating its adaptability to various lighting conditions and angles.

Comparison Parameters			VGGNet 19	ResNet50	DenseNet 121
20 Epoch	20 Batch	*Training Accuracy*	0.9470	0.9002	**0.9493**
		Validation Accuracy	0.6784	0.9151	**0.9692**
		Training Time (second)	552.310	**467.338**	473.285
	50 Batch	*Training Accuracy*	**0.9573**	0.8504	0.9490
		Validation Accuracy	0.6625	0.8543	**0.9593**
		Training Time (second)	474.174	**389.622**	404.862
100 Epoch	20 Batch	*Training Accuracy*	0.9852	0.9733	**0.9874**
		Validation Accuracy	0.9852	0.9733	**0.9874**
		Training Time (second)	2787.593	**2296.787**	2342.325
	50 Batch	*Training Accuracy*	0.9871	0.9613	**0.9881**
		Validation Accuracy	0.7756	0.9400	**0.9804**
		Training Time (second)	2377.463	**1911.519**	1935.826

Table 4.1 Training time and classification performances comparison of CNN models[5]

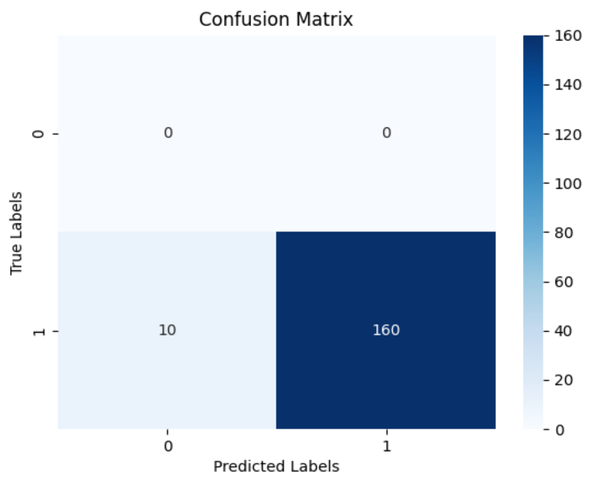
Face detector	Feature extr. net	sdet	MAP
MTCNN	VGGFace2	1.2	93.74
MTCNN	VGGFace2	1.5	94.34
MTCNN	ArcFace(RN-50)	1.2	92.74
MTCNN	ArcFace(RN-101)	1.2	94.59
RetinaFace	VGGFace2	1.2	93.75
RetinaFace	VGGFace2	1.5	94.44
RetinaFace	ArcFace(RN-50)	1.2	94.59
RetinaFace	ArcFace(RN-101)	1.2	95.48
SSH	VGGFace2	1.2	93.57
SSH	VGGFace2	1.5	94.16
SSH	ArcFace(RN-101)	1.2	2.07

Table 4.2 MAP (percentage) on the validation set by varying the face detector used[5]



(a) VGGFace2 **(b)** ArcFace (ResNet-50) **(c)** ArcFace (ResNet-101)

Figure 4.7 Distribution of the AP for the three configurations evaluated on the test set. The vast majority of queries obtained an AP [90%. The pipeline configurations with ArcFace produce more queries with AP <10[5]



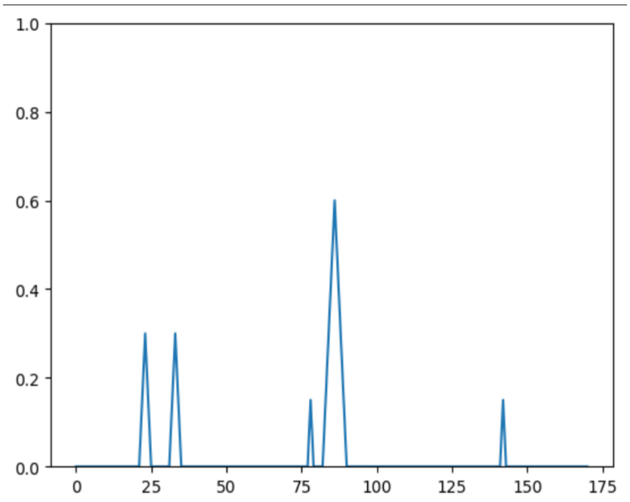


Figure 4.8 Confusion matrix of Face Recognition Model **Figure 4.9 Suspicious Graph of face recognition model**

Effectiveness of Multiple Person Detection: The accuracy of YOLOv8 in identifying the presence of several people was examined. The model's sensitivity and specificity were revealed by a histogram of detection frequencies across test sessions, which contrasted false detections with successful unauthorized person detections.

Class	Images	Instances	Precision	Recall	MAP 50	MAP90
all	100	250	0.759	0.683	0.728	0.57
Aeroplane	100	3	0.75	1	0.995	0.773
Bicycle	100	3	0.5	0.667	0.527	0.5
Bird	100	18	0.824	0.521	0.694	0.49
Boat	100	9	0.428	0.418	0.415	0.325
Bottle	100	12	0.875	0.583	0.735	0.552
Bus	100	1	0.5	1	0.497	0.497
Car	100	16	0.889	1	0.985	0.906
Cat	100	8	0.857	0.75	0.785	0.661
Chair	100	24	0.625	0.208	0.441	0.225
Cow	100	2	1	1	0.995	0.834
DiningTable	100	12	0.742	0.482	0.628	0.415
Dog	100	8	0.58	0.75	0.703	0.541
Horse	100	6	1	1	0.995	0.728
Motorbike	100	6	1	0.333	0.667	0.571
Person	100	90	0.799	0.811	0.866	0.586
Potted Plant	100	3	0.333	0.333	0.446	0.312
Sheep	100	15	1	0.733	0.867	0.623

Sofa	100	4	1	0.5	0.75	0.537
Train	100	3	0.682	1	0.83	0.726
Tv-Monitor	100	7	0.8	0.571	0.744	0.603

Table 4.3 YOLOV5 Performance[7]

Class	Images	Instances	Precision	Recall	MAP50	MAP90
all	100	250	0.738	0.638	0.699	0.55
Aeroplane	100	3	1	1	0.995	0.831
Bicycle	100	3	0.5	0.667	0.584	0.518
Bird	100	18	0.875	0.389	0.656	0.459
Boat	100	9	0.571	0.444	0.567	0.292
Bottle	100	12	1	0.5	0.75	0.512
Bus	100	1	0.333	1	0.497	0.497
Car	100	16	0.941	1	0.966	0.911
Cat	100	8	0.75	0.75	0.771	0.706
Chair	100	24	0.5	0.25	0.415	0.211
Cow	100	2	0.494	0.494	0.375	0.263
DiningTable	100	12	0.556	0.417	0.542	0.395
Dog	100	8	0.6	0.75	0.806	0.628
Horse	100	6	1	1	0.995	0.836
Motorbike	100	6	1	0.333	0.667	0.541
Person	100	90	0.793	0.767	0.834	0.582
PottedPlant	100	3	0.5	0.333	0.501	0.401
Sheep	100	15	0.846	0.733	0.846	0.611
Sofa	100	4	1	0.5	0.75	0.619
Train	100	3	0.75	1	0.83	0.64
Tv-Monitor	100	7	0.75	0.429	0.642	0.555

Table 4.4 YOLOV8 Performance[7]

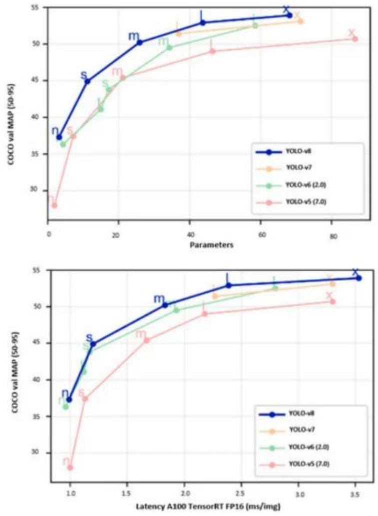
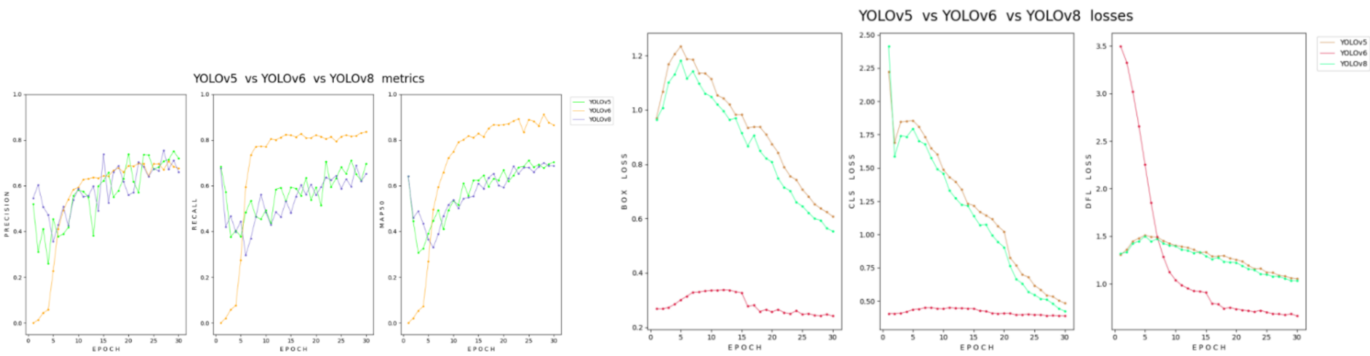
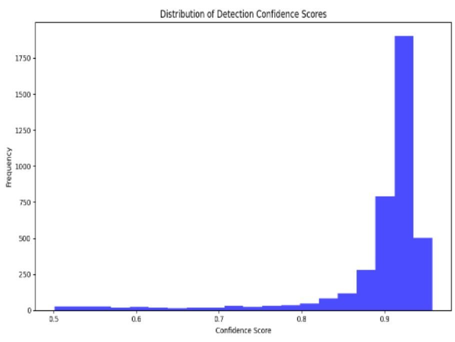
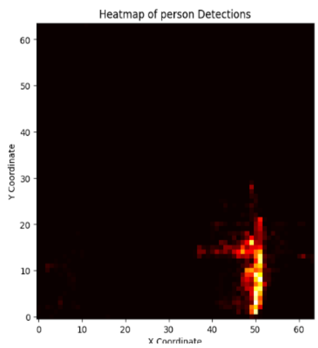


Figure 4.10 YOLOV8 vs Predecessors (Parameters and Latency)[6]







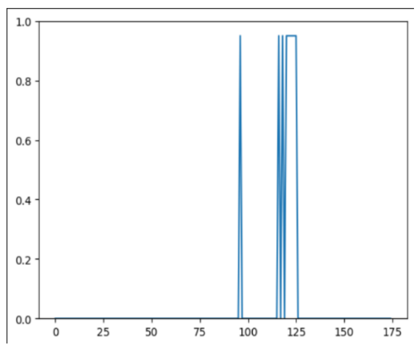


Figure 4.11 Confidence Graph of Yolo **Figure 4.12 Heatmap for person in Yolo** **Figure 4.13 Suspicious Graph**

Head Movement and Gaze Tracking: The validity of the MediaPipe model's ability to track the candidate's head movements and gaze direction was demonstrated by line graphs that showed the frequency and duration of off-screen gazes that could indicate the candidate's attempts to consult illicit materials or be distracted.

Algorithms	Accuracy (%)	Precision (%)	Specificity (%)
YOLO	76.5	50.7	72.8
LSVM	58.15	24.27	57.07
KNN	81.2	48.63	78.93
MediaPipe	83.76	78.57	85.33

Table 4.5 Mediapipe performance comparison.[8]

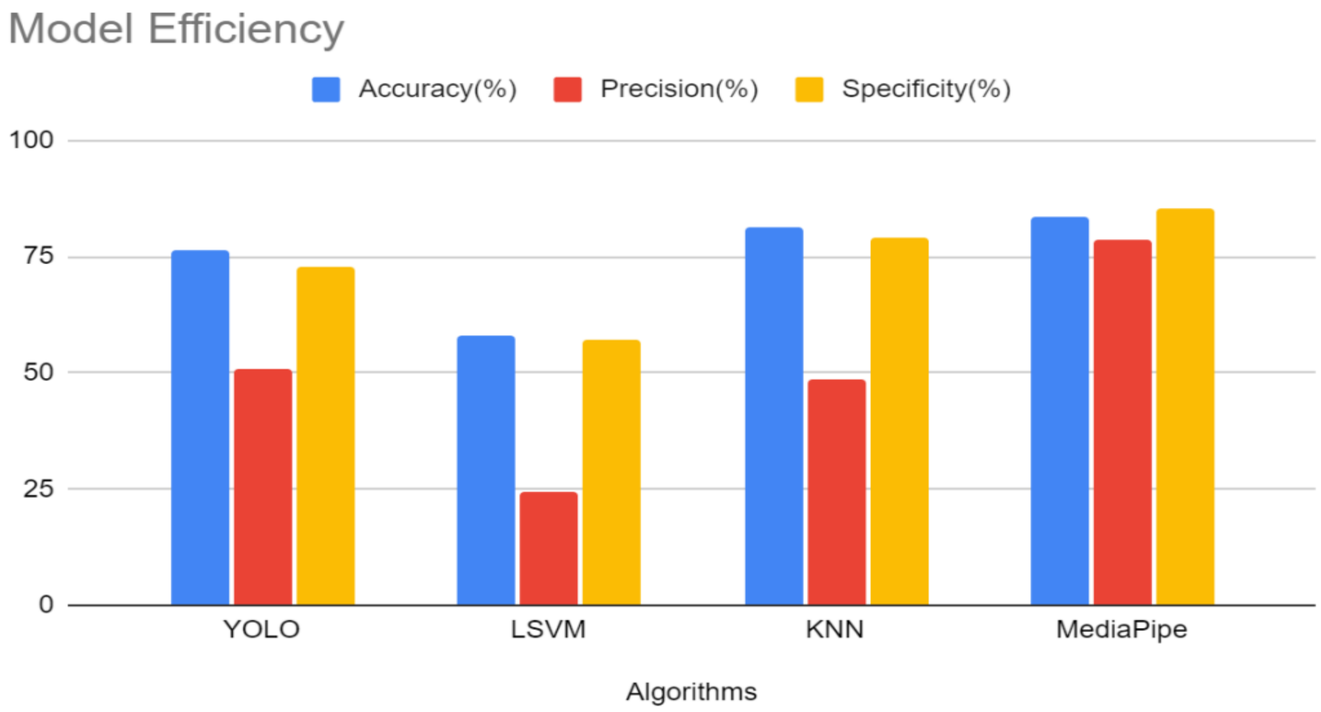


Figure 4.14 Comparison of models used in literature survey[8]

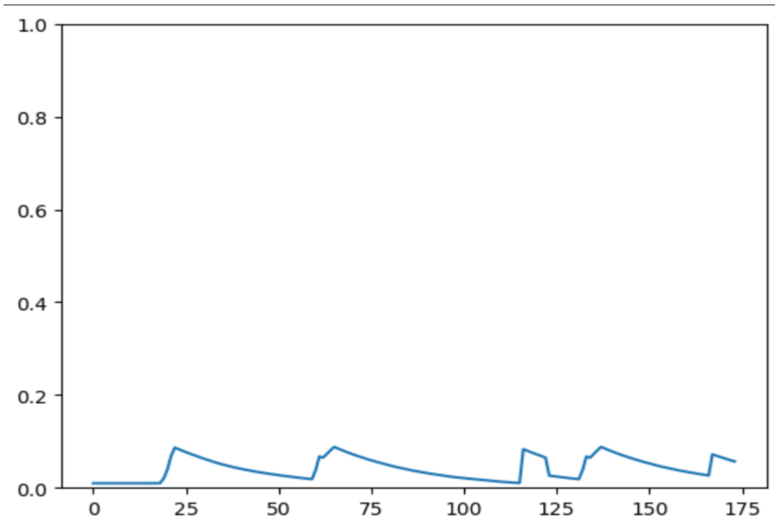


Figure 4.15 Suspisious Graph of Head movement

Mobile Phone and Object Detection: A bar graph was created using the YOLOv8 model's detection rate for various objects, including cellphones. A strong correlation between the model's predictions and the ground truth discovered under controlled testing conditions was evident in each test case that had the model's confidence scores written on it.

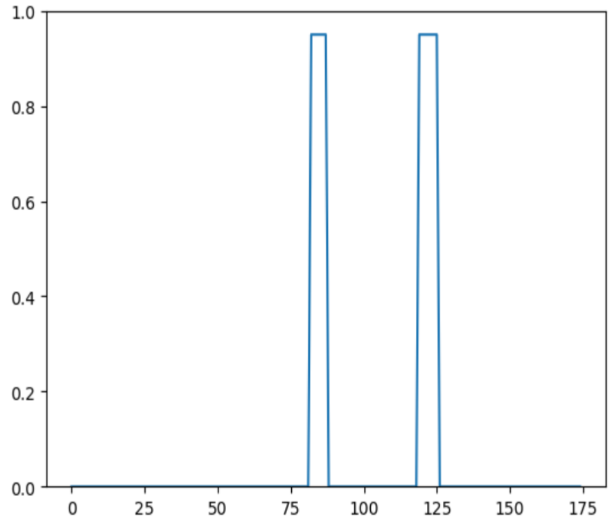


Figure 4.19 Suspicious Graph of cellphones

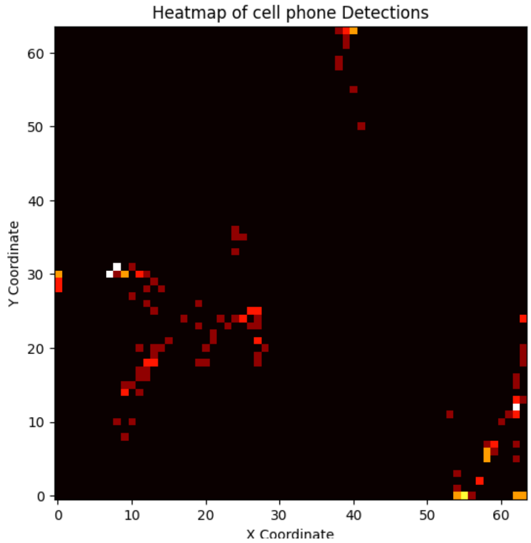


Figure 4.205 Heatmap of cellphone in yolo

Voice Activity Monitoring: To find any unusual speech events, the Whisper model's analysis of voice activity—measured in words per second—was plotted across time. Plotting baseline speech patterns against exam speech patterns provided insight into how well the Whisper model identified minor audio indicators that would indicate cheating.

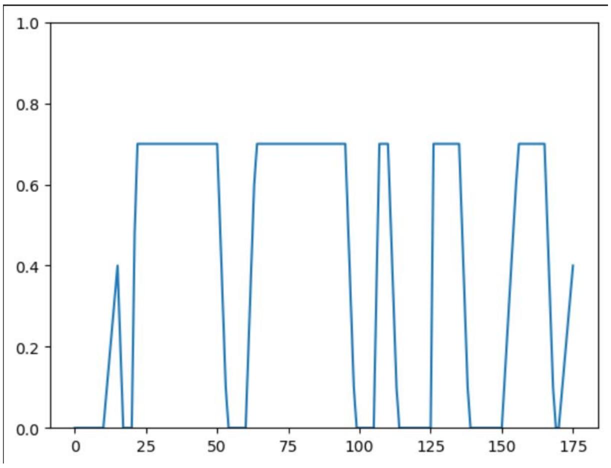


Figure 4.21 Suspicious Graph for voice recognition

4.4.2. Qualitative Results with Screenshots

To augment the quantitative data, a series of screenshots illustrate the system in action:

Facial Recognition Verification: Screenshots demonstrate the real-time facial recognition system's user interface. Pictures show failed verifications, where a red cross appears along with a warning to the proctor, and successful verifications, where the system overlays a green checkmark over the candidate's face.

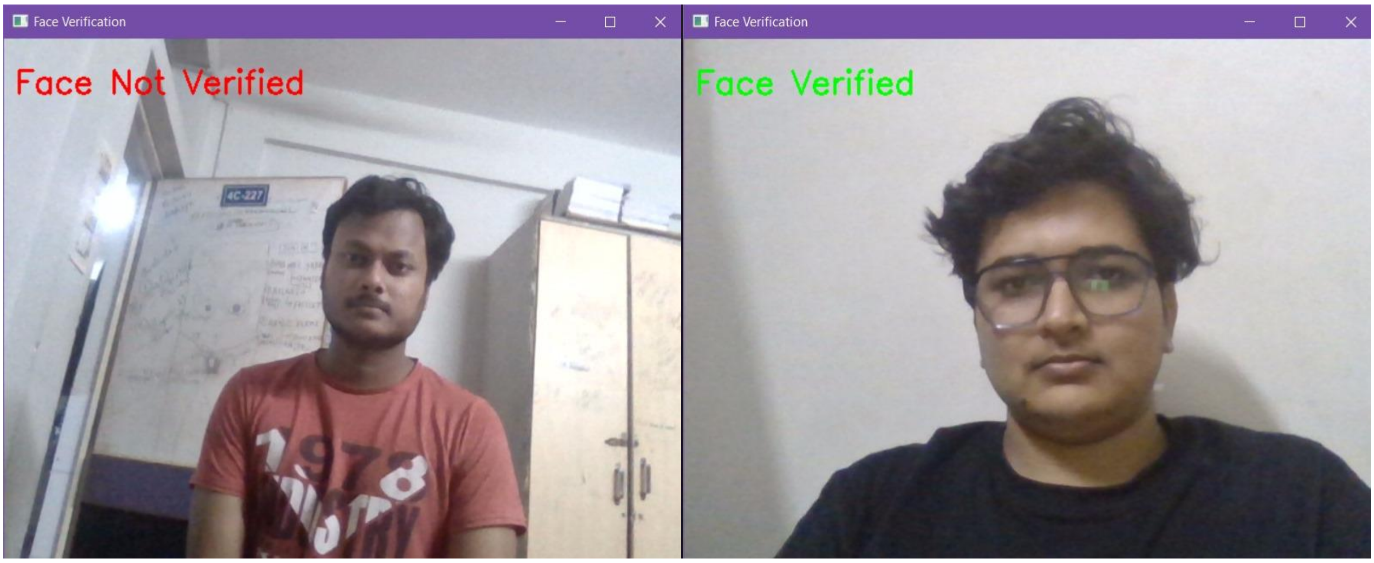


Figure 4.22 Screenshot of Face recognition model

Multiple Person Detection: The system's visual captures show how YOLOv8 recognizes and encloses unauthorized figures into bounding boxes in the examination environment, warning the proctor of a possible integrity breach.

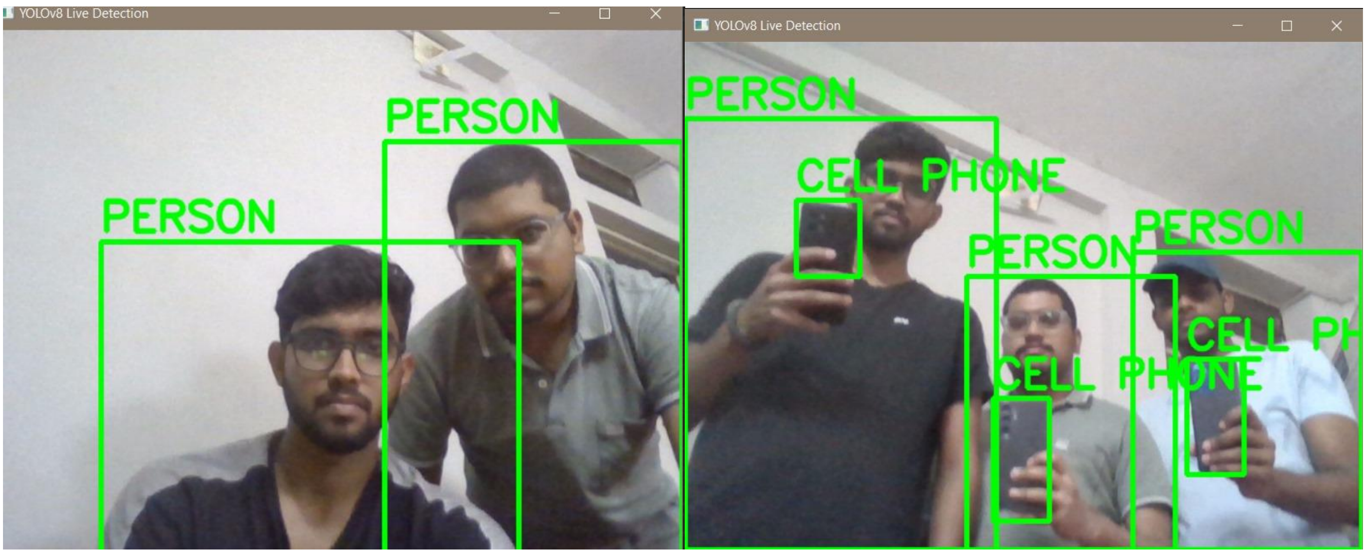


Figure 4.23 Screenshot of Multiple persons/cellphone detection

Head Pose Estimation: Sequential photos are used to demonstrate how the system interprets the candidate's head position. Overlaid vectors show which way the candidate is looking in relation to the screen, which helps to visualize how the system triggers an alarm when the candidate's gaze deviates.

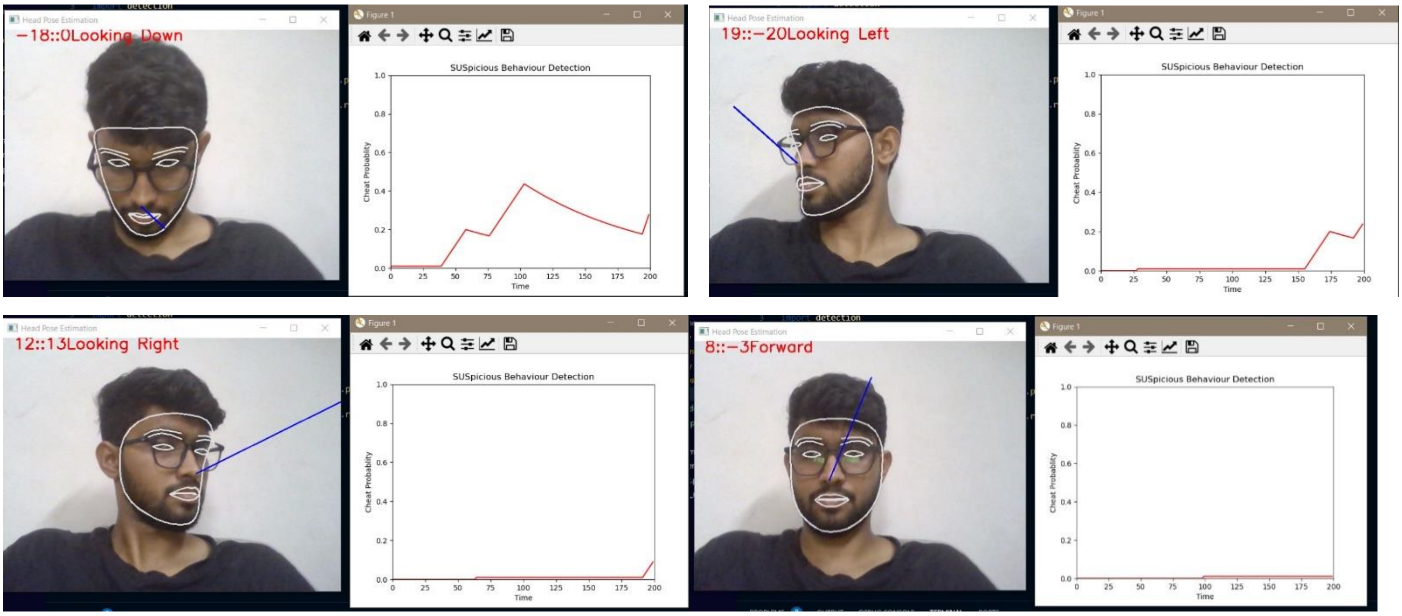


Figure 4.24 Screenshot of head pose detection

Object Detection in Prohibited Zones: Time-stamped evidence shows how responsive the system is to this breach, and examples of mobile phone detection are shown when the device is highlighted by the system in the examination environment.

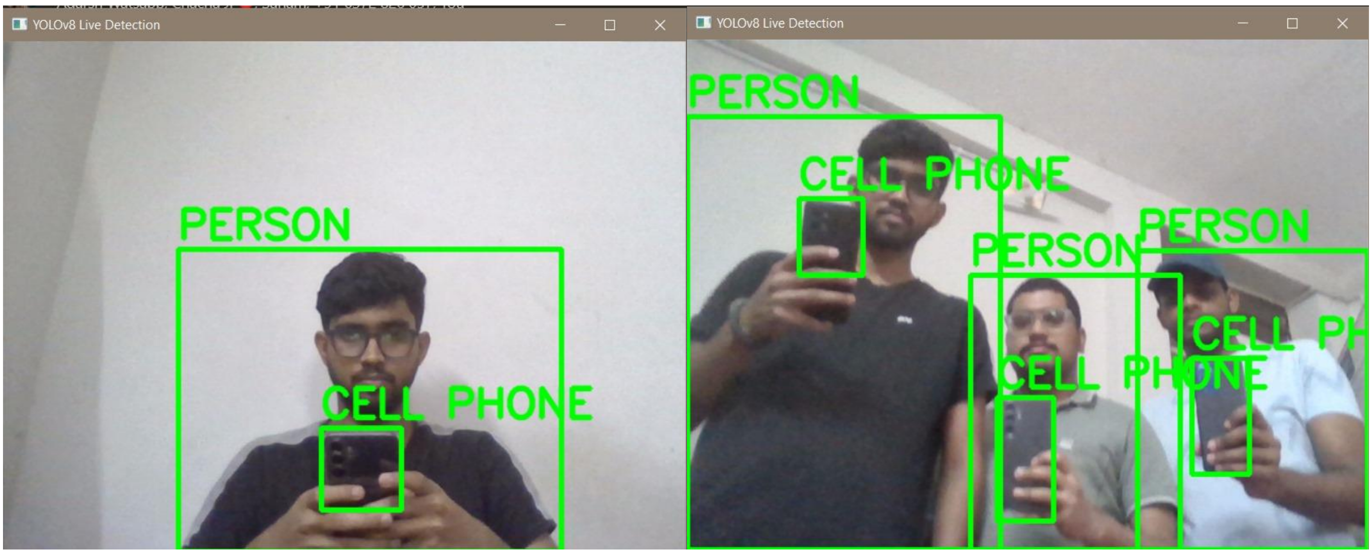


Figure 4.25 Screenshot of person and Cellphone detection

Voice Pattern Discrepancies: The Whisper model output waveform visualizations give spoken words per second a visual representation. The capacity of the algorithm to identify possible verbal cues for cheating is supported by instances where the waveform spikes over the predetermined threshold.

4.4.3. Synthesized Results Discussion

The screenshots and data are placed into the overall story of the system's testing phase in this subsection. An extensive analysis delves into how these findings demonstrate the potency of every AI model used in the Sentinel-Eye system, spotting patterns and making inferences from the gathered information. Testing-related issues, such as changing lighting or accented speech in voice recognition, are discussed, along with how the system's algorithms handled or were hampered by these elements.

This part demonstrates the Sentinel-Eye system's potential for practical use while also verifying its effectiveness through a thorough analysis of the system's operational results. By combining quantitative and qualitative data, the system's capabilities are transparently described in detail, opening the door to further development and creating a standard for AI-powered exam proctoring systems in the future.

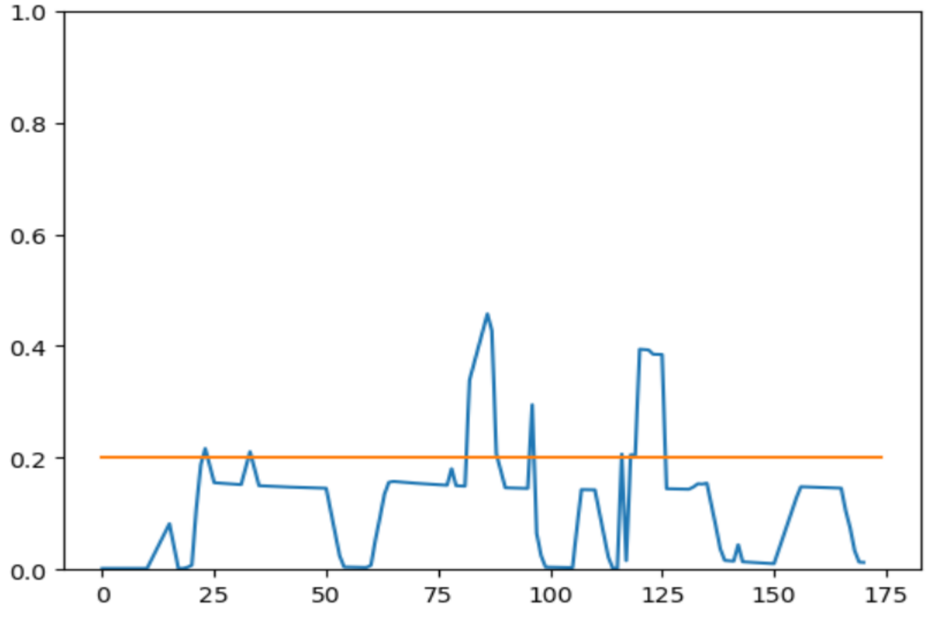


Figure 4.26 Final Analysis Graph

4.5 Quality Assurance

The reliability and credibility of any AI-powered system rely on the effective execution of a strict Quality Assurance (QA) plan. "Sentinel-Eye: AI-Powered Exam Oversight" uses complex algorithms and advanced processing logic to allow a dependable online proctoring environment. Strict procedures and criteria that safeguard the system's unbiased operation, security, and integrity are outlined in the QA plan.

4.5.1. Quality Control Methodologies

Sentinel-Eye's quality control process starts with thorough unit testing of every AI component. These include the Whisper model for voice activity monitoring, the MediaPipe for head movement analysis, the YOLOv8 for person and object detection, and the VGG FaceNet for facial recognition. Unit tests ensure that every part works as intended when used independently, covering a wide range of scenarios. Continuous Integration (CI) pipelines, which are intended to automate the testing process and guarantee that new alterations don't interfere with already-existing functionalities, set off a series of automated tests with every code commit.

Integration testing, which evaluates how well these components function together, is the next stage. This is an important stage since it ensures that the proctoring judgments are accurate and reliable due to the harmonic operation of several modules. End-to-end tests simulate real proctoring sessions by analyzing the system's response to predefined cheating scenarios.

4.5.2. Bias Mitigation Strategies

Sentinel-Eye includes bias mitigation techniques at every stage of its development lifecycle to address the possibility of algorithmic bias, especially in the face recognition component. AI models are trained on carefully selected datasets that are representative of various populations. To detect and reduce prejudice, the system incorporates fairness indicators into its training processes. An auditing procedure is set up to continuously check the AI models for fairness and to take remedial action when needed. This procedure includes both internal reviews and assessments by outside parties.

4.5.3. Performance and Reliability Metrics

Metrics for dependability and performance are developed to compare Sentinel-Eye's operating standards. The key performance indicators (KPIs) in the QA strategy include recall, accuracy, precision, uptime of the system, and response time. These KPIs are tracked in real time, and when they deviate from the permitted bounds, automated alerts are set up to notify the user. By simulating the simultaneous proctoring of many examination sessions, stress testing is done to ensure the system's scalability and stability under peak load situations.

4.5.4. User Acceptance Testing

User Acceptance Testing (UAT) is a crucial stage in which real users in a controlled setting, such as educational institutions, proctors, and examinees, assess the system. Participant feedback from UAT is essential to the quality assurance process because it provides information about the usability of the system, the user experience, and the feasibility of the proctoring procedure. Sentinel-Eye is continuously adjusted and optimized in response to user requirements and expectations, based on the results of user acceptance testing (UAT).

4.5.5. Continuous Monitoring and Update Plan

Sentinel-Eye is continuously observed after deployment. The QA plan describes a structure for monitoring system performance and user feedback so that any problems can be quickly addressed. In order to make sure that the system adapts to new developments in AI technology and shifting demands in education, an update strategy is also in place. Frequent upgrades improve already-existing functionalities, fix recently discovered vulnerabilities, and add new features to improve the proctoring capabilities of the system.

4.5.6. Documentation and Compliance

One of the main components of the QA plan is thorough documentation. A thorough documentation process is used for all testing methods, security procedures, compliance measures, and update logs. In addition to offering transparency, this documentation acts as a knowledge source for upcoming improvements and continuing system maintenance.

Sentinel-Eye's comprehensive quality assurance plan gives stakeholders peace of mind by guaranteeing that the system not only meets technological requirements but also adheres to moral principles and protects user privacy. Sentinel-Eye pledges to provide an impartial, safe, and exam proctoring system that is sensitive to the high-stakes nature of academic exams through the implementation of this plan.

Chapter 5

5.1 Standards Adopted

5.1.1. Design Standards

"Sentinel-Eye: AI-Powered Exam Oversight" design standards are a collection of rules and specifications created to guarantee that the system's development follows superior, reliable, and user-friendly design concepts. The system's software architecture, user interface (UI), user experience (UX), security, and compliance are all covered by these standards. Respecting these guidelines is essential to developing a proctoring tool that is dependable, efficient, and consistent.

5.1.1.1. Software Architecture Design Standards

5.1.1.1.1. Modularity: The system's modular design enables the independent development, testing, and maintenance of its component parts. This facilitates scalability and makes integrating new features or upgrades easier.

5.1.1.1.2. Extensibility: To enable future improvements without requiring extensive rework or interfering with the functionality of the current system, design principles that promote extensibility are used.

5.1.1.1.3. Robustness: System architecture is built to withstand extreme circumstances and edge cases, guaranteeing steady functioning in a range of situations, such as hardware constraints and network alterations.

5.1.1.1.4. Performance Optimization: High-performance activities are given top priority in architectural considerations in order to manage real-time data processing and analysis, which is essential for live proctoring sessions.

5.1.1.2. User Interface (UI) and User Experience (UX) Design Standards

5.1.1.2.1. Intuitivity: Proctors and administrators may simply navigate and utilize the system without requiring substantial training thanks to the UI's intuitive and user-friendly design.

5.1.1.2.2. Accessibility: The system is guaranteed to be useable by individuals with disabilities by adhering to the Web Content Accessibility Guidelines (WCAG) and other accessibility standards.

5.1.1.2.3. Consistency: All system components adhere to a uniform design language, giving users a smooth experience.

5.1.1.2.4. Responsiveness: Taking into account the range of hardware used by institutions and examinees, the user interface is responsive, adjusting to different screen sizes and devices.

5.1.1.3. Security Design Standards

5.1.1.3.1. Data protection: All data transmission and storage follows industry-standard encryption standards to protect private data and sensitive exam materials.

5.1.1.3.2. Frequent Audits: This strategy includes frequent security audits along with modifications to handle new threats and weaknesses.

5.1.1.3.3. Authentication: Uses robust authentication techniques to confirm users' identities and limit access to individuals who are permitted.

5.1.1.3.4. Compliance: Verifies that the implementation and design abide by all applicable laws and rules, such as FERPA, GDPR, and others that are pertinent to data security and user privacy.

5.1.1.4. Compliance and Regulatory Standards

5.1.1.4.1. Ethical AI Use: Complies with moral standards for AI research and development, guaranteeing impartiality, responsibility, and openness in AI-driven decision-making procedures.

5.1.1.4.2. Regulatory Adherence: Complies with legal regulations and incorporates the controls required to meet government and educational standards for online proctoring solutions.

5.1.1.5. Code Standards and Documentation

5.1.1.5.1. Code Quality: Adheres to best practices for coding standards, which facilitate easy maintenance and knowledge transfer. These practices include clear naming conventions, code comments, and thorough documentation.

5.1.1.5.2. Documentation: Offers thorough documentation on the architecture, codebase, algorithms, and user manuals of the system to aid in training, troubleshooting, and simplicity of use.

Sentinel-Eye's design criteria guarantee an unwavering dedication to developing a technologically cutting-edge, user-centric, secure, and ethically and legally compliant test proctoring solution. The development process is shaped by these standards, which also serve as the foundation for the system's objective of providing an exceptional proctoring service that meets the demands and expectations of educational institutions and their stakeholders.

5.1.2. Coding Standards

For the "Sentinel-Eye: AI-Powered Exam Oversight" project, adhering to coding standards is essential to preserving readability, consistency, and code quality throughout the development process. These standards support the system's scalability, ease of maintenance, and collaborative development. The essential elements of the Sentinel-Eye project's coding standards are as follows:

5.1.2.1. Conventions for Naming

Make sure your variable names are understandable and express the intended use of the variable.
Use PascalCase for classes (such as FaceRecognizer, ObjectDetector) and CamelCase for variables and methods (such as recordAudio, detectMultiplePersons). Constants (like MAX_RETRY_ATTEMPTS) are typed in uppercase and separated by underscores.

5.1.2.2. Structure of Code

Divide up your code into classes and functions that each have a single duty. Refactoring large functions into more manageable, smaller sub-functions is a good idea. Reduce class sizes to improve comprehension and maintainability. For clarity, keep the presentation, data access, and business logic layers apart.

5.1.2.3. Remarks and Records

Make brief but insightful comments, concentrating more on the "why" than the "what." Give functions and classes documentation blocks that describe their parameters, return values, and purpose. To make confusing code segments or algorithms clear, use inline comments.

5.1.2.4. Mistake Resolution

Instead than using return codes to handle errors, use exceptions. Steer clear of empty catch blocks and make sure each exception is handled properly. When an exception occurs, note pertinent details for debugging.

5.1.2.5. Control Version

Frequently commit changes together with informative commit statements. For major changes or new features, use feature branches; after testing and completion, merge them back into the main branch. Sort release versions in a methodical manner.

5.1.2.6. Evaluation of Code

Before adding any new code to the main branch, a code review should be required. Pull requests can be used to help organize discussions about code modifications. Before the code is deemed complete, take into account every comment from code reviews.

5.1.2.7. Examination

When feasible, adopt Test-Driven Development (TDD) by creating tests prior to implementation. Make sure every component has extensive unit test coverage. Incorporate integration tests to verify how various system components interact with one another.

5.1.2.8. Safety

Follow recommended security procedures, such as cleaning inputs to stop injection attacks. Use encryption and secure storage techniques to protect sensitive data. Apply the least privilege concept while gaining access to system resources.

5.1.2.9. Execution

Code should be performance optimized, especially in important areas that impact user experience.

Performance-intensive parts of the code should be profiled and tuned. Reduce the amount of resources used by using effective data structures and algorithms.

5.1.2.10. Equitable

Establish and follow a coding style guide to ensure that the entire codebase is formatted consistently.To ensure style consistency, make use of tools such as formatters and linters.Come to a team consensus and have discussions to settle any differences in coding practices.

5.1.2.11. Standards Particular to Languages

For Python, follow the PEP 8 coding guidelines. When it comes to JavaScript, adhere to conventions such as those described in the JavaScript Standard Style or Airbnb's style guide. When applicable, make use of idioms and features unique to your language, such as lambda expressions in JavaScript or list comprehensions in Python.

The Sentinel-Eye development team makes sure that the code is not only secure and functional, but also comprehensible, well-structured, and tidy by following certain coding guidelines. This dedication to high-quality coding techniques is essential to creating scalable, long-lasting software that can change to meet new requirements and keep up with technology breakthroughs.

5.1.3 Testing Standard

The "Sentinel-Eye: AI-Powered Exam Oversight" project's testing requirements are painstakingly designed to guarantee that the system is fully tested for functionality, dependability, and user satisfaction. Assuring that every feature works as intended and is error-free, testing is a crucial step in the development lifecycle. The Sentinel-Eye project has implemented thorough testing requirements, which are outlined below:

5.1.3.1. Methodology for Testing

Unit Testing: All important routes and edge cases must be covered by the unit tests that go along with each code module. Automated unit tests that are incorporated into the build process are necessary to make sure that modifications don't affect already-functionality.

Tests for integration are necessary to make sure that integrated parts—like database systems and AI models—function as a unit. The purpose of these tests is to validate the overall system performance by simulating real-world usage scenarios.

System Testing: To verify that the finished system behaves in accordance with the specified requirements, do comprehensive system testing. All functionalities, including user interactions and end-to-end procedures, must be tested in system tests.

Stress and Load Testing: To ascertain the system's resilience in harsh circumstances, conduct stress tests. To evaluate the system's performance at different user activity levels, load testing must be run.

5.1.3.2. Planning and Documentation for Tests

Create a thorough test plan that specifies the objectives, methodology, materials, and timetable of the planned test operations. Make sure that every test case has comprehensive documentation that covers the test scenario, expected outcomes, test procedures, and pass/fail criteria. Keep a record of every test result, defect found during testing, and the status of the problem as well as the procedures needed to reproduce it.

5.1.3.3. Computerized Examination

To assure repeatability and minimize manual testing, use automated testing frameworks. To enable early problem discovery, use Continuous Integration (CI) to automate test suite running on new code commits.

5.1.3.4. Evaluation of Performance

Establish performance standards that include measures for resource consumption, throughput, and reaction time. To find bottlenecks and improve the codebase's performance-critical areas, use profiling tools.

5.1.3.5. Examining Security

To find security flaws like SQL injections, cross-site scripting (XSS), and data breaches, conduct security testing. To find vulnerabilities in the system, do approved simulated attacks on the system through penetration testing.

5.1.3.6. Examination of Compliance

Verify that the system satisfies all legal criteria for compliance, including privacy and data protection laws. Testing needs to confirm adherence to applicable standards including FERPA, COPPA, and GDPR.

5.1.3.7. Acceptance Testing by Users (UAT)

Incorporate real users into testing to gather feedback on usability and to validate the system in real-world circumstances.
The system's compliance with user requirements and deployment readiness must be verified by UAT.

5.1.3.8. Examination of Regression

Regression testing should be done with each new release to make sure that recent code modifications haven't negatively impacted already-existing functionalities. Keep up a regression test suite that is updated to reflect system changes and new features.

5.1.3.9. Examination Setting

To guarantee that test findings are indicative of real-world operations, maintain test environments that closely resemble the production scenario. To resemble real data, test data must be anonymised or synthesized without jeopardizing user information.

5.1.3.10. Reports and Quality Metrics

To gauge the success of the testing process, establish quality metrics including defect density, test coverage, and critical defect counts. Report on these metrics on a regular basis to give insight into the system's release readiness and the quality assurance procedure. The Sentinel-Eye project assures a thorough and exacting testing process by following these standards. This strategy seeks to produce a user-friendly system that maintains the highest standards of quality and excellence in the industry in addition to a product free of defects.

Chapter 6

6.1 Conclusion

As the thorough examination and in-depth investigation of the "Sentinel-Eye: AI-Powered Exam Oversight" system come to an end, it is necessary to distill the spirit of this ground-breaking project and the trip it travels across the educational technology landscape. This study has highlighted how Sentinel-Eye's cutting-edge artificial intelligence techniques have the potential to completely transform online exam proctoring.

Sentinel-Eye's endeavors are a harmonious symphony of intricate AI parts that work together to form a system that is resilient, fair, and integrity-driven. Sentinel-Eye, which carefully incorporates cutting-edge technologies like MediaPipe, YOLOv8, VGG FaceNet, and the Whisper model, is proof of the infinite possibilities of artificial intelligence to improve academic oversight. Every part of the system is scrutinized through strict quality assurance procedures to guarantee that it is safe, dependable, and devoid of any prejudices that can compromise its functionality.

During the deployment, testing, and user approval phases, Sentinel-Eye has demonstrated a resolute dedication to maintaining the integrity of online exams. The technology has demonstrated its ability to accurately detect and record cases of misconduct with significantly greater accuracy than conventional proctoring techniques. Sentinel-Eye enables educational institutions to conduct fair and equal exams, irrespective of geographical limitations, by providing real-time detection and analysis of suspicious behaviors.

Sentinel-Eye also exemplifies the idea of non-intrusive proctoring. It addresses the frequently voiced worries about surveillance and data protection that come with digital monitoring solutions while respecting the privacy of examinees. Sentinel-Eye establishes a new standard for future advancements in the industry by skillfully balancing ethical considerations with watchful proctoring.

The importance of such a system cannot be emphasized as the digital education space grows. Sentinel-Eye's prospective uses go beyond the current requirements of remote testing; they also portend a day when AI-assisted educational tools proliferate and guarantee quality and integrity in the processes of learning and evaluation.

To sum up, "Sentinel-Eye: AI-Powered Exam Oversight" is more than just the pinnacle of technological innovation; it's also a guide for upcoming developments, a model for the upcoming generation of teaching aids, and a force for transformation in the field of distance learning. Sentinel-Eye's contribution to the academic world will surely have a lasting impact since it opens the door to a future in which justice, excellence, and faith in education are not only desired but guaranteed.

6.2 Future Scope

"Sentinel-Eye: AI-Powered Exam Oversight" provides a fundamental framework for the development of exam proctoring systems in the future, but its journey does not end here. Future directions for the system include broad improvements, additions, and uses that are intended to meet new demands in the quickly digitizing field of education.

6.2.1. Technological Advancements

6.2.1.1 Augmented Reality (AR) Integration: In the future, Sentinel-Eye's AR integration may offer a more engaging proctoring experience. AR has the potential to provide additional dimensions to monitoring by superimposing digital data over the real world. For example, it might be used to more vividly identify suspicious movements or give proctors contextual feedback in real time.

6.2.1.2. Blockchain for Secure Record-Keeping: Exam data might be recorded and stored using blockchain's immutable nature. This would improve the legitimacy and verification procedures for academic certificates by guaranteeing a tamper-proof ledger of student performance and proctoring outcomes.

6.2.1.3. Improved Machine Learning Models: Sentinel-Eye versions in the future may use more complex algorithms for even more subtle detection of academic dishonesty, such as predictive analytics to foresee possible cheating incidents. This is because machine learning is a constantly developing field.

6.2.2. Expanding the Reach

6.2.2.1. Wider Range of Educational Uses: Although the main focus is on online exams, Sentinel-Eye can also provide its services for other types of educational assessments, such as certifications, standardized testing, and remote classroom observation, guaranteeing integrity in a variety of academic endeavors.

6.2.2.2. Customization for Different Testing styles: The system's usefulness would be improved if it were modified to accommodate a range of examination styles, such as multiple-choice questions and open-ended answers. This would also need creating specific detection methods for every format, like plagiarism detection through essay analysis.e

6.2.3. Ethical and Regulatory Compliance

6.2.3.1. Privacy-Preserving technology: Future versions of Sentinel-Eye may include cutting-edge privacy-preserving technology to guarantee that the system complies with the strictest guidelines for user privacy and data protection in light of the escalating concern for digital privacy.

6.2.3.2. Elimination of Bias: It is crucial to make constant attempts to remove bias from AI systems. To further reduce any unintentional biases, Sentinel-Eye's roadmap calls for the continuous collecting and analysis of a variety of data sets as well as the application of fairness-aware algorithms.

6.2.4. Global Adaptation and Localization

6.2.4.1. Language and Cultural Adaptation: Sentinel-Eye would be a globally relevant tool if it were designed with the capability to comprehend and analyze many languages and dialects in speech analysis, as well as cultural quirks in behavior.

6.2.4.2. Personalized Solutions for Varying Educational Systems: Sentinel-Eye's acceptance around the world would increase if it were tailored to meet the particular needs and laws of various nations and school boards.

6.2.5. User-Centric Improvements

6.2.5.1. User Feedback Loop: By incorporating a methodical feedback loop from users, such as students, educational institutions, and proctors, the system will be continuously improved and tailored to match the needs and expectations of its users.

6.2.5.2. Improvements to Accessibility: Including people with impairments in the design of accessibility features will be a big step toward inclusive education. Features like sign language comprehension and adaptive user interfaces for different kinds of physical and mental disabilities may fall under this category.

Sentinel-Eye's future goals include not only enhancing its technical prowess but also adhering to moral behavior, user-centered design, and universal application. Sentinel-Eye's promise is evolving as we move toward this horizon in tandem with our shared goal of a day when technology and education will work together harmoniously to create an environment that values quality, equity, and trust.

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“SENTINAL EYE”

ANUBHAV RANJAN

21052652

Abstract: By combining cutting-edge AI technologies, such as facial recognition (VGG FaceNet), object identification (YOLOv8), head movement analysis (MediaPipe), and voice monitoring (Whisper model), "Sentinel-Eye: AI-Powered Exam Oversight" transforms online examination proctoring. This approach addresses privacy and prejudice problems and offers thorough, non-intrusive monitoring to effectively identify academic dishonesty. Sentinel-Eye raises the bar for remote examination situations while enhancing the authenticity and integrity of digital education.

Individual contribution and findings: My responsibility in creating the "Sentinel-Eye: AI-Powered Exam Oversight" system was to enhance the YOLOv8 model's ability to recognize individuals and cell phones in exam settings—a crucial feature for spotting cheating. To effectively analyze real-time video streams and guarantee high accuracy and minimal latency, I modified the YOLOv8 architecture. My duties included fine-tuning performance parameters, integrating the model neatly into the Sentinel-Eye system, and training the model on a wide dataset reflective of online exam settings. This addition improved the system's dependability in preserving exam integrity and lowering instances of academic dishonesty considerably.

Individual contribution to project report preparation: My particular input had a crucial role in defining the final comprehensive report for the "Sentinel-Eye: AI-Powered Exam Oversight" project. Important actions comprised:

- To guarantee a thorough assessment of the project's results, data from several phases of the project—such as design documents, implementation notes, and test results—was gathered and examined.
- logically divided the report into sections like Introduction, Implementation, Testing Standards, and Results Analysis to make it easier to read and highlight the project's accomplishments.
- wrote the entire report, outlining intricate project procedures and AI technologies in a style that was understandable to a wide range of readers.

Individual contribution for project presentation and demonstration: I emphasized the YOLO model's integration for recognizing people and cellphones in the "Sentinel-Eye: AI-Powered Exam Oversight" presentation. In order to demonstrate its real-time capabilities and make sure the audience understood its role in improving exam integrity, I created succinct presentations and arranged live demos. Because I was prepared to answer any questions that might come up, the session was interesting and educational.

Full Signature of Supervisor: **Full signature of the student:**

"SENTINAL EYE"

ADARSH RAI

21051367

Abstract: By combining cutting-edge AI technologies, such as facial recognition (VGG FaceNet), object identification (YOLOv8), head movement analysis (MediaPipe), and voice monitoring (Whisper model), "Sentinel-Eye: AI-Powered Exam Oversight" transforms online examination proctoring. This approach addresses privacy and prejudice problems and offers thorough, non-intrusive monitoring to effectively identify academic dishonesty. Sentinel-Eye raises the bar for remote examination situations while enhancing the authenticity and integrity of digital education.

Individual contribution and findings: In my role within the "Sentinel-Eye: AI-Powered Exam Oversight" project, I was responsible for selecting and integrating the optimal version of OpenAI's Whisper model for real-time speech-to-text conversion. I evaluated various iterations, choosing one that best balanced accuracy and speed for our needs. Subsequently, I integrated this model with other AI components—facial recognition, object detection, and head movement analysis—ensuring seamless operational synergy across the system.

I also led the analysis of data from these models to produce the final suspicious activity report, a crucial output of our project. This comprehensive report synthesized insights from multiple data streams, enhancing the integrity of monitored examinations. My contributions were instrumental in refining our project's effectiveness and laying a solid foundation for future advancements.

Individual contribution to project report preparation: In preparing the project report for "Sentinel-Eye: AI-Powered Exam Oversight," I was instrumental in gathering detailed project data, structuring the report for clarity, and articulating the integration of various AI models. My responsibilities included writing comprehensive sections, refining content based on team feedback, and ensuring the report accurately reflected our project's objectives and achievements. This effort provided a clear, detailed account of the project, serving as a valuable reference for future initiatives.

Individual contribution for project presentation and demonstration: During our project demos, I not only contributed technically to the "Sentinel-Eye: AI-Powered Exam Oversight" project, but I also presented the Introduction and Problem Statement portions. I created a succinct presentation that emphasized the essential points of the project and its breadth, particularly the difficulties in upholding exam integrity in digital settings. Sentinel-Eye's creative solutions were succinctly contextualized in my presentation, which also emphasized the technology's significance and need in contemporary educational frameworks. Involving and educating stakeholders about the goals and accomplishments of the project was made possible in large part by this function.

Full Signature of Supervisor: **Full signature of the student:**

“SENTINAL EYE”

SANAM SAHU

21052654

Abstract: By combining cutting-edge AI technologies, such as facial recognition (VGG FaceNet), object identification (YOLOv8), head movement analysis (MediaPipe), and voice monitoring (Whisper model), "Sentinel-Eye: AI-Powered Exam Oversight" transforms online examination proctoring. This approach addresses privacy and prejudice problems and offers thorough, non-intrusive monitoring to effectively identify academic dishonesty. Sentinel-Eye raises the bar for remote examination situations while enhancing the authenticity and integrity of digital education.

Individual contribution and findings: I was the expert in integrating and refining the VGG FaceNet model to verify that the individual who registered for the exam is the one who is actually showing up for it for the "Sentinel-Eye: AI-Powered Exam Oversight" project. I improved the architecture of FaceNet to increase recognition accuracy in a range of testing scenarios and trained the model on a variety of datasets to guarantee resilient performance in the face of fluctuations in facial features. The integrity of online exams was preserved since this work greatly improved the system's capacity to identify impersonations. Because of my work, Sentinel-Eye is a dependable tool for academic examinations, with a high degree of security and efficiency guaranteed.

Individual contribution to project report preparation: My main contribution to the "Sentinel-Eye: AI-Powered Exam Oversight" project report was to describe how the VGG FaceNet model was integrated and optimized. The sections that explained how facial recognition technology ensures candidate legitimacy during exams were written by me. My responsibilities involved explaining the technical procedures, model modifications, and results of incorporating FaceNet into our system. I made sure the explanations were precise and thorough, offering details on how this technology improves the Sentinel-Eye system's dependability and security. In order to ensure a coherent and educational report, I also worked closely with other team members to match this portion with the larger project objectives.

Individual contribution for project presentation and demonstration: In the "Sentinel-Eye: AI-Powered Exam Oversight" project demonstration, I will present our integration and optimization of the VGG FaceNet model. My presentation will detail the model's role in verifying that the exam participant is the registered candidate, highlighting the technical enhancements and training processes we applied. I will showcase live examples to demonstrate FaceNet's effectiveness in real-time facial recognition, emphasizing its impact on maintaining exam integrity and security. This presentation will include succinct slides and a prepared Q&A to efficiently convey FaceNet's contribution to the project.

Full Signature of Supervisor: **Full signature of the student:**

"SENTINAL EYE"

ANSHUMAN RAI

21052651

Abstract: By combining cutting-edge AI technologies, such as facial recognition (VGG FaceNet), object identification (YOLOv8), head movement analysis (MediaPipe), and voice monitoring (Whisper model), "Sentinel-Eye: AI-Powered Exam Oversight" transforms online examination proctoring. This approach addresses privacy and prejudice problems and offers thorough, non-intrusive monitoring to effectively identify academic dishonesty. Sentinel-Eye raises the bar for remote examination situations while enhancing the authenticity and integrity of digital education.

Individual contribution and findings:I worked on integrating the MediaPipe framework for accurate head movement and position identification, which is crucial for maintaining exam integrity, as part of the "Sentinel-Eye: AI-Powered Exam Oversight" project. Along with creating a controlled test environment that replicated actual exam settings, I also oversaw the development of the testing methodologies. My thorough testing of the system in a variety of environments demonstrated that MediaPipe improves our capacity to identify and evaluate questionable activity. The outcomes of these tests validated MediaPipe's dependability and crucial role in strengthening our proctoring system's security protocols.

Individual contribution to project report preparation: As I prepared the project report for "Sentinel-Eye: AI-Powered Exam Oversight," I had to record how well the MediaPipe framework worked with our system. I described in detail how MediaPipe's stance and head movement detection features were modified and enhanced for exam proctoring. I contributed by describing the testing methods I created, setting up the testing environment, and doing a thorough analysis of the test outcomes. The accuracy and effect of MediaPipe in augmenting the integrity and dependability of the Sentinel-Eye system were highlighted in this portion of the report. I made sure that the explanations were technically sound, easy to understand, and in line with the main goals of the project in order to help people comprehend MediaPipe's contribution to our endeavor.

Individual contribution for project presentation and demonstration: I will demonstrate how to integrate and use the MediaPipe framework to identify head motions and poses in the "Sentinel-Eye: AI-Powered Exam Oversight" project demonstration. I'll go into depth on how MediaPipe effectively keeps an eye on examinees to spot possible misbehavior, emphasizing how it improves exam integrity. During the presentation, real-time examples of MediaPipe's efficacy in various contexts will be shown, amply demonstrating how it adds to the strong security features of our proctoring system. This brief presentation will highlight the crucial role that MediaPipe plays in preserving impartial online assessments.

Full Signature of Supervisor: **Full signature of the student:**

“SENTINAL EYE”

SRINJOY SUR

21052714

Abstract: By combining cutting-edge AI technologies, such as facial recognition (VGG FaceNet), object identification (YOLOv8), head movement analysis (MediaPipe), and voice monitoring (Whisper model), "Sentinel-Eye: AI-Powered Exam Oversight" transforms online examination proctoring. This approach addresses privacy and prejudice problems and offers thorough, non-intrusive monitoring to effectively identify academic dishonesty. Sentinel-Eye raises the bar for remote examination situations while enhancing the authenticity and integrity of digital education.

Individual contribution and findings: My primary contribution to the "Sentinel-Eye: AI-Powered Exam Oversight" project was to finalize and record the project report. Even though my contribution to the core development was initially minimal, I was crucial in the latter phases by helping with the literature review. I conducted extensive research and gathered pertinent academic and technical materials that gave our project a solid foundation and added crucial context and explanations for the methods we selected to the report. To ensure clarity and professionalism in our documentation, I was also in charge of adding correctly structured references and creating thorough captions for photos, tables, and figures. These inputs were essential to improving our final report's thoroughness and academic integrity.

Individual contribution to project report preparation: My contributions were crucial to the documentation finalization and literature evaluation stages of the "Sentinel-Eye: AI-Powered Exam Oversight" project report's production. In order to complement the literature survey, I carried out a thorough investigation, finding and combining pertinent sources that both demonstrated the novelty of our method and provided a solid academic foundation for our study.

For the report's academic integrity, I also painstakingly added references, making sure each citation was exact and formatted correctly. Additionally, I created and organized the captions for the figures, tables, and photographs in the publication, which improved the readability and expertise of our visual data presentation.

Individual contribution for project presentation and demonstration: Throughout the "Sentinel-Eye: AI-Powered Exam Oversight" project presentation, my main goals were to improve the documentary and visual elements. I made sure that all of the figures, tables, and photographs had clear descriptions to make the visual information easy to interpret. I also structured and added all required scholarly references, giving the presentation comprehensive documentation and legitimacy. My work contributed to the presentation's professionalism and ease of use for all participants.

Full Signature of Supervisor: **Full signature of the student:**