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Snoop: A Real-Time AI-Based Online Exam Invigilation Systems

Prof. Abha Pathak[1], Mr. Tanmay Shingote[2], Mr. Shivam Kumar[3], Mr. Mahesh Sumb[4], Mr. Omkar Sawant[5]

[1,2,3,4,5]Department Of Computer Engineering, Dr. DY Patil College Of Engineering And Innovation Pune, India

Abstract

Technology is growing day by day. we are seeing rapid shift towards online education and they are various platforms developed for online teaching. But no determined structured product/application design to have a well-based exam system ie: no malicious activities happen. So, Snoop - An AI integrated system designed to look at the student or peoples on there assesment test to be conducted by the eductional platforms or the organizations for hiring candidates. The system designed for this activity has integration of various AI models for real-time detection for malicious activities, ie: spoofing, unauthorized faces. it also catthers the lovalid sound that can be occured during examination. This system working makes a significance work in the online assesment by providing the secure, reliable and automated system.

Keywords: Online Exam Monitoring, artificial intelligence (AI), Real Time Invigilation, Computer Visions, Auto anomaly detection, Automated Invigilation.

I. INTRODUCTION

Online learning has increased rapidly in recent years. Many online tools have been adopted in schools, colleges and universities. surfaces used to educate and administer exams. This shift has became at the time of the COVID-19 pandemic, when students and teachers was being forced to remain at home. While online exams are comfortable and easy to cheat on, they also introduce one huge issue, which is how can we make. sure that students can't copy? [1], [2]

A teacher or invigilator can observe the students in a classroom and ensure that there is fairness. But in an online exam, there is no physical person to keep an eye on the student. This creates potential for dishonesty, so affecting the fairness and also the integrity of the examination. In order to address this problem, numerous systems are currently being created through Artificial Intelligence (AI) to supervise students when taking online exams. [3]–[5]

These are artificial intelligence-powered invigilation sys- tems, which are capable of utilizing a student. screen, screen, microphone and webcam to monitor their actions. during the test. The system is capable of identifying whether or not the student is looking. out of the screen excessively, conversing with a person, utilizing opening their phone or attempting to open other websites. [6], [7] Some facial movements and eye direction are even tracked to be captured by systems. suspicious behavior. [8] There are, too, privacy issues, since the students are being monitored and recorded during their exams. Not every student feels comfortable with that. [3]There are also concerns about privacy because the students are being watched and recorded during their exams. Not all students feel comfortable with that. [1] There are other systems

that can also be biased or fail to work. well for everyone.
Due to all these reasons, it is worth studying and. realize how AI-based exam monitoring systems do. work. We must see what means are employed, how true they are, and what the problems still are. By doing this, we can learn what to do to better these systems and to make them better. just, honest, and ethical towards students. [2], [4]

II. Literature Review

A. Online Learning and Assessment Developmental Issues.

During the period, the shift to online learning increased at a high pace. the COVID-19 era which also changed the way exams were conducted. Flexibility and access were given through online examinations to the students in the various realms, yet simultaneously. They cast grave reservations as to fairness and cheating and fairness and identity checks. [2] It is due to this that numerous researchers have proposed technical means as well as the procedures to control malpractices and at the same time value student privacy and trust. [1], [4]

B. Student & Teacher Perspectives

The impact of online exams is one of the biggest spheres of work that people have focused on in the past and are considered by learners and educators. Butler-Henderson et al.
[1] reviewed several studies and have reported that students. in most cases preferred the convenience and ease of online tests. Meanwhile, they were afraid of how to work with proctoring software and potential technical breakdown. Teachers, But we are more anxious to ensure how to ascertain that. the right student was trying to pass the test and whether the surveillance equipment would be efficient. This indicates a gap between usability and security, the latter must be considered. proportional in any proctoring system.

C. Impact of Proctoring Tools

Some of the investigations have concentrated on the efficacy of monitoring technologies in lessening malpractice. Hylton et al. The study by [3] compared webcam-based proctoring and exams, which resulted in increased perceived difference by the students who were being monitored to cheat, but exam scores did not vary significantly. This implies that the putting off impact is more under the control of the growing scholar. act according to the perceived danger compared to the establishment of complete absence. dishonesty.

D. Protocols & Institutional Experiences

At the institutional level, Patael et al. [2] explained that. In the case of Tel Aviv University, proctoring was at scale. pandemic. Their results indicated that software itself is unable to guarantee exam integrity. Better outcomes were attained. when there are no ambiguous rules, employee education, adequate instructions to the students, and contingency, in case of technical failure, were instigated. Another conflict was also brought to light by them, which is between instructors who prefer the normal proctored exams and students who demand another one. assessments, which means that technology should be harmonized. pedagogy and communication.

E. Technical Developments in Proctoring

Technologically, the contemporary systems tend to take the shape of modern. are a combination of several techniques like face recognition, gaze and tracking of head movement, object searching, and lock-out of browser-down features [6], [7], [9]. These systems are capable of automatic alarm in case there is a different individual, when the student recurrently diverts his gaze, or when forbidden things are noticed. While the methods enhance precision, they also experience difficulties. as fake positives due to lighting or quality of camera, and as many possible loopholes as used by students. Therefore, such systems should be used as support for the researchers. Rather than being dependent on teachers, they are expected to use this as a compliment to them. [4], [5]

F. Research Gaps & Current Contribution

In spite of these developments, there are still gaps in the current systems. Most of them are dependent on one performing mode of detection. increases the chances of error and incorrect praxis. Large-scale communication and planning studies also focus on that. and protocols are not any less important than algorithms. [2] Furthermore, problems such as privacy, accessibility, and stress in students tend to be frequent. [1], [3]

The present project suggests overcoming these issues. A proctoring system that is based on artificial intelligence and reaches several integrations. layers of evidence. It is a combi- nation of biometric authentication, gaze and object tracking, browsing history tracking, and response similarity checks. The system is unlike the previous methods in that it is not dependent on the conventional ones. created to provide readers with explicit reportable reports to instructors. instead of com- puterized evaluations. This way, it aims to make large-scale examinations secure as well as practical by online examination deployment. [4], [6], [9]

III. Methodology

The Snoop review also notes the algorithmic differences in the analysis that is done. Merits and flaws of existing methods of online exam monitoring. A stratified architecture is used, the modules of which are numbered. helps in total integrity checking of exams, minimizing dependency. This is the method that is in line with what is there. literature that is proving the multi-modal systems to be more reliable than single-mode solutions. [6] [4], [8]

A. Face Detection

Haar Cascade classifier is implemented in real time. detection. They are lightweight and quick thus rendering them alive. proctoring. Nevertheless, the accuracy reduces as the face is smaller. curved or ought to be dull or black. to overcome this, more challenging. Substitutes such as MediaPipe or Dlib might be considered in the future labor to be more robust. [9], [10] The Haar Cascade classifier uses AdaBoost algorithm in learning a cascading network of decision nodes by rectangular features. This pyramidal design is permitting rejection of non- face regions to be fast, therefore facilitating real time. detection possible to be made [11]. A weighted sum of weak The final decision function is called ht classifiers:

$$H(x) = sign\left(\sum_{t=1}^{T} \alpha_t h_{t(x)}\right)$$

Where:

- $H(x)$: $Final\ strong\ classifier$
- α_t : $Weight\ assigned\ to\ weak\ classifier\ h\_t$
- $h_t(x)$: $Weak\ classifier\ at\ iteration\ t$
- T : $Total\ number\ of\ weak\ classifiers$

One such feature detector that is believed to be stronger is the Histogram of Oriented Gradients (HOG) which is a feature description that is used to acquire the geometric object gradients in the immediate intensity gradients. [12]

$$G = sqrt\left(\left(\frac{\partial I}{\partial x}\right)^2 + \left(\frac{\partial I}{\partial y}\right)^2\right)$$

$$\theta = \tan 2\left(\frac{\partial I}{\partial y}, \frac{\partial I}{\partial x}\right)$$

Where:

- G - The magnitude of the gradient.
- Θ - The gradient orientation.
- I - The intensity value of the image.
- $\frac{\partial I}{\partial x}$ - The partial derivative of the intensity along x-direction.
- $\frac{\partial i}{\partial y}$ - The partial derivative of the intensity along y-direction.

All these algorithms would normally perform a detection accuracy of 85-92% when there is good light conditions. [13]

B. Gaze and Head Movement Tracking

To see that a student is losing his eyesight off the screen, The system uses Face Landmark Detection to identify key. round the eyes, and then there is straight geometric. Ratio. Method to calculate the direction of the gaze. This method determines a ratio of position of iris with respect to corners of the eyes:

$$r = \frac{d_{left}}{d_{right}}$$

Where:

- $r \quad - Computed\ geometric\ ratio.$
- $d\_left \quad - Distance\ between\ the\ center\ of\ the\ iris\ and\ the\ left\ side\ of\ the\ eye.$
- $d\_right \quad - Distance\ between\ the\ center\ of\ the\ iris\ and\ the\ right\ corner\ of\ the\ eye.$

The method is economical of resources but not as precise as high tech eye-tracking models. Although it is enough in simple monitoring, it can produce natural head false positives. mobility, and emphasizing the

necessity to balance usability and accuracy. [1], [3], [8]

C. Mobile/Phone Detection

YOLO (You Only Look Once) is the single stage object detectors that are considered as the fastest as well as the most accurate. The model takes a single step to process the entire image, and at the same time, the prediction of both class labels and bounding boxes is made. Such a one-pass characteristic makes it especially appropriate to use in real time.

The loss function of YOLOv5 has three separate parts that in turn train the network:

$$L_{total} = \lambda_{box} L_{box} + \lambda_{obj} L_{obj} + \lambda_{cls} L_{cls}$$

Where:

- $L\_total \; - \; Total\ loss\ of\ the\ model.$
- $L_{box} - Localization\ loss, measuring\ error\ in\ predicted\ bounding\ box\ position\ and\ size.$
- $L\_obj \; - \; Objectness\ loss, indicating\ whether\ an\ object\ is\ present\ in\ a\ bounding\ box.$
- $L\_cls \; - \; Classification\ loss, measuring\ error\ in\ class\ prediction.$
- $\lambda\_box \; - \; Weight\ for\ localization\ loss.$
- $\lambda\_obj \; - \; Weight\ for\ objectness\ loss.$
- $\lambda_{cls} \; - \; Weight\ for\ classification\ loss.$

YOLOv5 can use this multi-component loss function, which enables it to generate loss and find out a good balance between quickness and high accuracy, transforming it into a potent object-recognition device such as a mobile phone in real time. [2], [8], [14]

D. Cheat Scoring and Alerts

The system combines individual detections into a weighted scoring system that is based on rules. I believe it is a relatively open and adjustable strategy, which is a enormous advantage over those black-box AI models, which no one can explain in a way. Its drawback is only that we have to pick the weights manually, making it unfeasible to make the system match the scenarios of different exams. [4], [7]

E. Browser-Level Monitoring

On the client do we have event listeners that intercept the resizing of tabs and the opening of full screens and suspicious key presses. These are tricks that are effective in preventing simple cheating over the internet in a decent level. The issue is that smart users can rely on virtual machines or change the devices so that they can squeeze through the browser tracking should be only the successful one and not the primary barrier. [5], [9]

F. Additional Considerations

Although there are plagiarism applications cited in literature such as k-shingling and similarity analysis, they are not incorporated in the latest version of Snoop. This is likely the case since we are still working on the core audit engine, although there is certainly the opportunity to add more features to the system, particularly where the content similarity becomes important, such as open-ended essay tests. [1] [6], [10]

Overall, Snoop demonstrates that an agreement to bring together a blend of the lightweight but complementary algo- rithms can render exam monitoring tougher. High efficiency, modularity, and explainability are much welcomed, and open problems still remain the false positives, environmental variability, privacy concerns, and the flexibility of the scoring rules to suit the various contexts. [2], [4], [8]

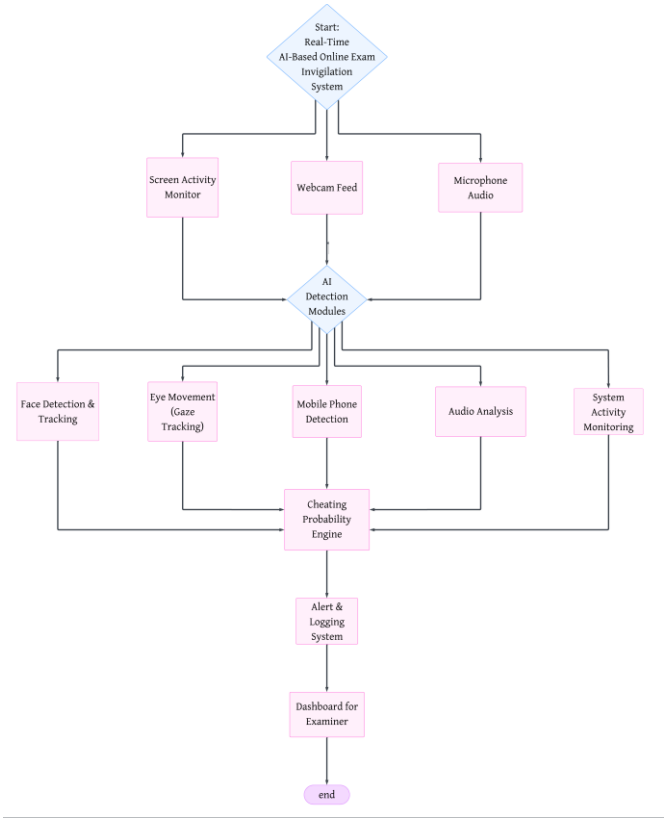

Fig. 1. Overall architecture of the Snoop AI-based online exam invigilation system.[15]

IV. Experimental Results

Snoop AI based online invigilation framework was tested by capturing real time output screen shots as different algorithms were tested in the framework. Each of the figures explains how the system distinguishes and follows a variety of objects including faces, mobile phones and user behaviour in real-time condition.

A. Face Detection and Tracking

Face-detection module was relatively tested as illustrated in Figure 2, on Haar Cascade and HOG based algorithms. The HOG algorithm is more resilient to small head rotations, but the Haar Cascade has a higher frame rate, with a maximum of 35.7 vs 24.3 FPS respectively of the HOG algorithm, which is slower.

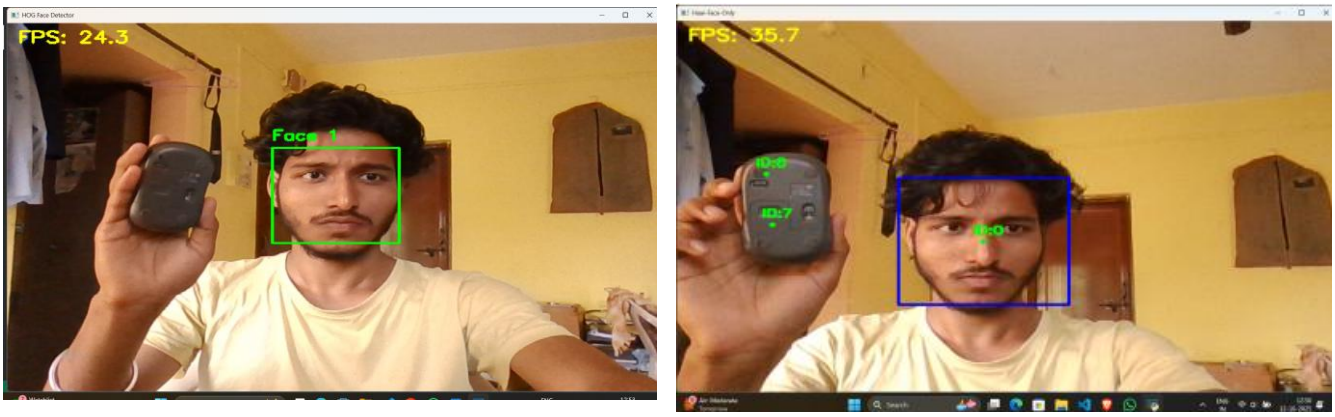

Fig. 2. Comparison of Haar Cascade and HOG-based Face Detection Algorithms.

B. Mobile Phone Detection using YOLOv8

This paper compared and contrasted the detection of mo- bile phones with the use of YOLOv8 and SSD algorithms to detect and identify handheld devices when doing online exams. Figure 3 shows that the YOLOv8 exhibited a stronger parameter of detection faith and concentration under varied light conditions, when compared to the SSD model that had a greater inference frequency when using the CPU based systems. YOLOv8 which had the lowest mAP of 89.3 in
29.8 FPS compared to the SSD model of 89.3 in 29.8 FPS, is more efficient in real-time applications in low-resource- endowed devices.

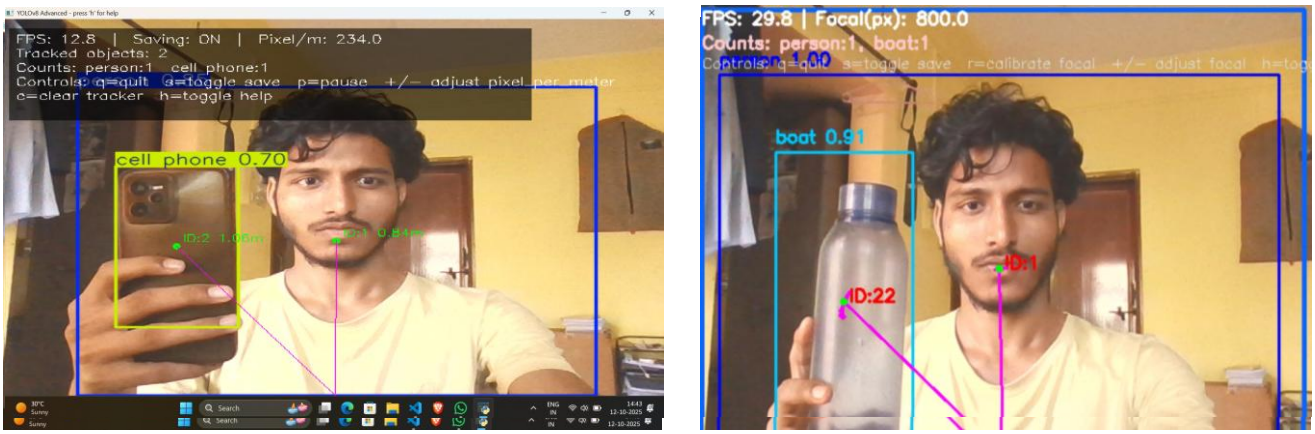

Fig. 3. Comparison of YOLOv8 and SSD Object Detection Algorithms.

C. Eye Movement and Concentration Detection

Facial landmark tracking and geometric ratio was applied as a method of concentration detection that analyses the gaze direction, as well as, eye aspect ratio (EAR). The system differentiates the state of Focused and Distracted in real time as shown by the states Focused and Distracted. The module has an average accuracy between 78 percent to 86 percent when the frames are 29 per second, which proves effective in terms of loss of attention in online examinations.

D. Audio Anomaly Detection using Fourier Transform and Speaker Identification

To control the illegal conversations or the surrounding voices, a combination of both Fourier Transform method and speaker recognition algorithm was used. This system carries out real time analysis of audio at all time to ensure that there are no deviation in the voice pattern of the primary enrolled speaker.

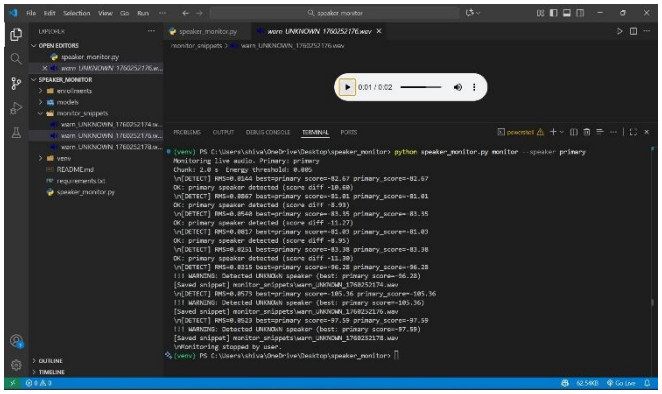

Fig. 4. Audio detection & unknown speaker identification.

Figure 4 shows that the identifications of unknown speakers creates alerts and the audio fragments are automatically stored to be reviewed later. As shown in Figure 4, unknown speakers generate warnings and audio is automatically saved for review.

E. System Implementation Details

The most important algorithms employed in each of the modules of the Snoop invigilation system are listed in Table I in detail along with a notion of their respective computational requirements.

Module	Algorithm Used	Resource Usage
Multiple Face Detection	Haar Cascade / HOG	Low–Medium
Mobile Phone Detection	YOLOv5 / YOLOv8	Medium
Eye Movement Tracking	Geometric Ratio Method	Low
Audio Anomaly Detection	Fourier Transform + Speaker Identification	Medium
Browser Activity Monitoring	JavaScript Event Listeners	Low
Cheat Scoring Mechanism	Weighted Rule-Based System	Low

TABLE I

OVERALL SUMMARY FOR ALGORITHMS

All the modules are factors in maintaining efficient, low-latency monitoring and at the same time ensure high invigilation coverage.

V. FUTURE DIRECTIONS

The version of Snoop that now exists proves the way lightweight. and online monitoring can be done by

designing modular algorithms. examinations effectively. Nevertheless, there are a number of areas that are open. for further development.

1) The adoption of deep learning models in terms of being more advanced. I would interact with an attractive face and stare to minimize false positives. was due to the poor lighting, head motion, or low quality. cameras. Previously, it has been established that multimodal. Deep-learning-based frameworks can go a long way towards making a good imprint. outperform classical method of detection. [6], [8]
2) Behavior fusion Multi-modal A significant direction is behavior fusion. Currently, Snoop addition of outputs of modules is done with the help of a rule-based scoring system. Future work could employ The fusion models are machine learning based which are learning the connection between indicators like face detection, gaze, browser events, deviation, and mobile phone presence. Smart AI has been developed by other methods. more adaptive based proctoring systems to obtain enhanced adaptability in various exam situations. [7], [9]
3) Cases of plagiarism and similarity detection must be laid in subsequent versions. Literature highlights the appli- cations like k-shingling, MinHash, LSH, etc. between semantic similarity to name collusion and near-duplicate answers . Integrating NLP techniques can also be used to increase robustness of essay-type as well as descriptive assessments. [6], [10].
4) Privacy-forfeiting design is still a significant cause of consideration. Research findings indicate that students tend to be nervous regarding On-spyware. On tools, encryption can be applied for device processing. These fears could be solved with the help of umbrella moni- toring levels. but keeping the institutional trust. Trans- parency in reporting is also important to enhance the acceptance. [1], [3]
5) Improving capability to withstand various environments is correct and necessary. There are unstable conditions inthe real world like internet, low cost computing, and common rooms. Institutional fallback mechanisms and staff have been demonstrated to assist in this. Comprehension of the fundamental concepts of succession as well as training and demonstrating the message requires a clear communication process of training, and clear communication is a key element of succession since understanding the basic concepts of succession and communicating the message clearly necessitates a clear communication process successful deployment. [2]

To sum up, the main tasks of future research about Snoop should be to pursue making it system not only tougher but also wiser and is more fair. more transparent. Integrat by enhancing the detection accuracy. PA NLP-based technologies, human privacy, and assurance. explainability, Snoop is capable of developing into a holistic solution. to easily conduct secure and student friendly online tests.

VI. Conclusion

The shift to digital education has transformed how we learn and assess, bringing convenience but also new challenges in protecting academic integrity. Traditional exam halls gave way to online platforms, which opened doors to cheating risks that can undermine the value of qualifications. Our system, Snoop, addresses this gap with a layered, AI-driven approach. It uses computer vision for identity checks, gaze tracking, and object detection, alongside audio analysis for unusual sounds. But its strength lies in supporting not replacing human invigilators. By providing evidence-based alerts, Snoop ensures educators

remain in control through a balanced "human in the loop" model. Still, ethical concerns like privacy, data security, bias, and student stress must be addressed. Fairness can also be affected by internet speed or device quality. That's why transparency, clear policies, and respect for student rights are essential. Looking ahead, Snoop aims to improve accuracy, reduce false positives, and adopt explainable AI to make flagged behaviors easier to understand. The vision is a fair, reliable, and less intrusive system that integrates seamlessly into Learning Management Systems. In short, safeguarding integrity in online exams requires both technology and human judgment. Snoop doesn't replace trust—it helps build it, en- suring digital education earns the same respect as traditional learning.

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