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Implementing an Ai-Driven Proctoring System: Real-Time Detection of Disruptive Sounds and Unauthorized Visual Infractions

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ABSTRACT
Online proctoring systems have become essential in educational and professional environments, especially as remote learning and assessments gain prominence. This study presents an innovative AI-based proctoring system designed to enhance online exam integrity by addressing two primary challenges: disruptive sounds and unauthorized visual infractions. The methodology comprises three stages: Data Collection, AI Model Development, and System Integration. In the first stage, sound samples and images of infractions were gathered to build a robust training dataset. The second stage involved developing two specialized models: a Convolutional Neural Network (CNN) for sound detection and a YOLOv4 model for visual infractions. Performance metrics – including accuracy, precision, recall, and false positive rates – were evaluated, with sound detection achieving 92.5% accuracy and visual detection reaching 94.7%. In the final stage, the system was deployed and tested in a simulated exam environment. Results revealed the model's reliability in detecting exam disruptions in real-time, with high responsiveness and minimal false positives. This study underscores the potential of AI in online proctoring, promoting fairness and reducing academic dishonesty.
Keywords*: AI-based proctoring, disruptive sound detection, unauthorized items, online exams, Convolutional Neural Network (CNN), YOLOv4, real-time monitoring*

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I. INTRODUCTION

The rise of online education and remote examination formats has introduced challenges to maintaining examination integrity and security(Bhvsp & Balabhadrapatruni, 2024). As educational institutions and organizations increasingly turn to virtual learning platforms, the demand for effective proctoring solutions has become essential. Traditional proctoring methods, which rely on continuous human monitoring, are resource-intensive and can fall short in detecting subtle disruptive behaviors. In response, artificial intelligence (AI) presents a promising solution, automating key aspects of online proctoring to strengthen exam security and promote fairness(Genemo, 2022; Wakchaure et al., 2023).This study addresses two primary areas of concern in online proctoring environments: disruptive sounds and unauthorized items. Disruptive sounds – suchas human conversations, loud machinery, and alarms – posesignificant threats to the examination atmosphere and can compromise focus and performance(Negi et al., 2024; Nurpeisova et al., 2023). Likewise, the presence of unauthorized items, including electronic devices, study aids, and other materials, enables cheating opportunities that traditional proctoring methods struggle to eliminate entirely(Daniel & Caleb, 2024). Therefore, an effective AI-driven solution can improve security, allowing for the detection and prompt response to potential infractions without requiring human intervention(Mewada et al., 2024).

The system developed in this study integrates sound and visual detection capabilities, offering a dual-component solution that monitors the environment comprehensively during exams. The study's methodology involves three critical stages: data collection, AI model development, and system integration. In the data collection stage, sound and visual datasets were compiled and categorized to ensure comprehensive coverage of typical exam-setting variations. The sound dataset comprised disruptive and benign sounds, including human speech, alarms, and typing, while the visual dataset included images of unauthorized items like mobile devices, study aids, and reflective surfaces. This phase was crucial to ensure that the models would effectively distinguish between benign and disruptive elements in live examination scenarios.The subsequent AI model development stage involved two different architectures tailored to the nature of sound and visual detection tasks. For sound detection, a Convolutional Neural Network (CNN) was used to process spectrograms, generated through Short-Time Fourier Transform (STFT), and trained on augmented data to enhance the model's resilience to real-world variances(Negi et al., 2024; Potluri et al., 2023). Visual detection employed YOLOv4, a popular model for real-time object detection, which was trained on annotated images of common infractions(Maoeretz & Agustinus, 2024; S. Sharma et al., 2024). The combined system aimed to meet high-performance standards, ensuring proctors could trust its capabilities.

Lastly, the integration stage focused on deploying the models within a proctoring framework equipped with microphones and cameras to enable real-time monitoring. This setup involved API functionalities to facilitate sound and image processing, a user interface for alerting proctors about detected infractions, and system settings for a seamless user experience during exams(Bommireddy et al., 2023; P. Sharma, 2023). The integrated system was tested in a simulated exam environment to assess accuracy, precision, and response efficiency.The findings of this study contribute to a growing body of research on AI-assisted proctoring. High accuracy and precision levels were recorded across disruptive sound and visual infraction detection, validating the feasibility of such systems for educational institutions. This study represents an essential step toward safer, fairer, and more reliable online examinations, ensuring academic integrity in digital learning spaces.The objective of this paper is to present an AI-based model that can effectively filter disruptive sounds and conduct preliminary scans for infractions. By addressing these two critical areas, AI-enhanced proctoring systems can significantly improve the reliability and acceptance of online assessments. This research aims to contribute to the development of a more comprehensive online proctoring framework that meets the demands of remote learning environments while prioritizing accuracy and user experience.

II. RELATED WORKS

Genemo (2022) introduces L4-BranchedActionNet, a 63-layer convolutional neural network (CNN) model derived from VGG-16, aimed at detecting suspicious activities during examinations. Through feature optimization and the application of an Ant Colony System (ACS), the model achieves impressive accuracy rates of 92.99% on the CUI-EXAM dataset and 89.8% on the CIFAR-100 dataset, thereby validating its robustness in identifying potential misconduct. Shkodzinsky and Lutskiv (2022) conduct a comprehensive analysis of existing identity verification algorithms for electronic learning environments, leading to the design of a targeted system tailored for the LMS ATutor platform. Their implementation of effective face detection and recognition algorithms has demonstrated success in real educational settings, supporting the practical adoption of their system. Thombare et al. (2022) propose an automated proctoring system designed to enhance online exam security, particularly in response to the heightened need for reliable remote assessment methods during the COVID-19 pandemic. This system effectively detects behaviors such as "looking left" and logs infractions, automatically submitting exams if misconduct surpasses predetermined thresholds, thus overcoming the limitations of traditional video invigilation methods.

Antoshchuk and Breskina (2023) present InternVideo, a specialized AI-based proctoring model aimed at analyzing student behavior during online learning. This model emphasizes both physical activity and hygiene, incorporating static (learning-focused) and dynamic (physical activity) modes, supported by a tailored prototype dataset.Fidas (2023) investigates credibility challenges in online examinations within higher education, identifying critical threats and proposing models and countermeasures for learning management systems. A case study of TRUSTID, an intelligent identity management system, showcases its effectiveness against impersonation and receives high usability ratings. Nurpeisova et al. (2023) explore the increasing prevalence of online education and the associated challenges in preventing academic dishonesty during remote exams. They develop Proctor SU, an AI-based proctoring system that integrates CNN, R-CNN, and YOLOv3 models. Notably, YOLOv3 demonstrates optimal performance at 45 frames per second, facilitating real-time face recognition and enhancing overall exam integrity.

Potluri et al. (2023) propose the Attentive System, an automated AI-based proctoring solution designed to bolster online exam integrity. This system employs live video monitoring, incorporating face detection, spoofing checks, and head pose estimation, achieving a remarkable accuracy rate of 0.87 in real-time evaluations. Yamuna et al. (2023) tackle the significant challenges associated with identity verification and proctoring in online examinations. Their proposed Auto-Proctoring system utilizes a combination of face recognition, mouth detection, audio monitoring, and various cheating prevention techniques to ensure a secure and cheating-free examination environment.Daniel and Caleb (2024) introduce an AI-proctored exam portal paired with a mobile companion app to enhance academic integrity in online learning contexts. Their system promotes safe exam administration, real-time monitoring, and detailed reporting, ensuring transparency and fairness in assessment practices.

Mewada et al. (2024) emphasize the challenges posed by secure academic examinations in the face of increasing remote learning. They propose an integrated AI-based system capable of detecting cheating, recording evidence, and providing a secure, cost-effective solution for universities. Negi et al. (2024) also focus on the challenges of academic integrity within the context of remote learning. They advocate for an integrated AI-based proctoring system that detects and reports exam cheating, thus providing a secure and economically viable solution. Sharma et al. (2024) present an automated AI-based proctoring system specifically addressing the challenges faced in online examinations. Utilizing YOLO and FaceNet technologies, their system enhances identity verification and object detection, achieving a 2.28% improvement in accuracy while maintaining user-friendly interfaces and real-time alerts for proctors.

III. METHODOLOGY

This study implemented an AI-based proctoring system with two primary components for real-time detection of disruptive sounds and identification of unauthorized items during online exams. The methodology was divided into three stages: data collection, AI model development, and system integration.

Stage One: Data Collection

Sound and visual datasets were collected to ensure the model's ability to accurately distinguish between typical and disruptive elements in a testing environment. A range of sources and controlled simulations contributed to this collection.

Sound Data Collection: The sound dataset included samples from open-source audio libraries and manual recordings representing varied environments. Sounds were categorized into disruptive and benign types, where disruptive sounds could interfere with the examination process and benign sounds typically do not(Niharika & Nayak, 2023; Shkodzinsky & Lutskiv, 2022). Table 1 shows a total of 2,620 sound samples that were collected to ensuring the model could accurately classify sounds across real-world scenarios.

Table 1: sound samples across real-world scenarios.

Sound Category	Sound Type	Source	Total Samples	Description
Disruptive Sounds	Human Speech	Open audio libraries	500	Recorded conversations, single speaker, and group chatter
	Alarms	Open audio libraries	200	Alarm bells, fire alarms, sirens
	Loud Machinery	Recorded sounds	150	Power drills, construction equipment
	Door Slamming	Controlled recordings	120	Slamming doors of various sizes
	Traffic Noise	Recorded sounds	300	Honking, engine revving, street noise
Benign Sounds	Birds Chirping	Open audio libraries	400	Background bird sounds from common areas
	Typing	Controlled recordings	250	Typing on mechanical and membrane keyboards
	Background Music	Open audio libraries	180	Low-volume music with no vocals
	Soft Conversations	Recorded sounds	220	Low-volume indoor conversations
	Ambient Indoor Noise	Controlled recordings	300	HVAC systems, light humming, and general room noise

Visual Data Collection: The visual dataset helped the model detect unauthorized items, such as electronic devices and study aids, commonly found in testing settings(Fidas et al., 2023; Thombare et al., 2022). Images were either sourced from licensed databases or captured manually in controlled environments(Antoshchuk & Breskina, 2023). A total of 1,040 images covered various infractions, helping the model accurately detect unauthorized items in live examination settings as shown in Table 2.

Table 2: various infractions or unauthorized items in live examination settings.

Infraction Type	Subcategory	Source	Total Images	Description
Unauthorized Devices	Mobile Phones	Licensed databases	150	Mobile devices in view, on tables, or in examinee's hand
	Smart Watches	Licensed databases	120	Smartwatches visible on wrists or tables
	Laptops/Tablets	Controlled environment	100	Laptops/tablets on or near testing area
Physical Study Aids	Books/Papers	Controlled environment	200	Textbooks, notes, and papers on desks
	Calculators	Licensed databases	80	Unauthorized calculators visible on table
Non-compliant Background	Posters/Whiteboards	Controlled environment	100	Posters or whiteboards with potentially helpful content
	Visual Clutter	Licensed databases	130	Backgrounds with excessive items or decorations
	Reflections	Recorded images	70	Mirrors or reflective surfaces in view
Other Infractions	Unauthorized People	Recorded images	90	Additional people entering or visible in the room

Stage Two: AI Model Development

The sound detection model and visual detection model (YOLOv4) were developed to distinguish between disruptive and benign elements effectively.A Convolutional Neural Network (CNN) architecture was chosen for the sound detection model due to its effectiveness in analyzing audio spectrograms(Satre et al., 2023). The model's development included these steps:

- **Spectrogram Generation:** Audio data was preprocessed by normalizing and segmenting clips. Using Short-Time Fourier Transform (STFT)(Mahmood et al., 2022), spectrograms were generated, providing a visual frequency representation crucial for model training.
- **Data Augmentation:** Background noise, pitch adjustments, and other augmentation techniques were used to make the model robust against real-world variations.
- **Model Training:** The CNN model was trained using a combination of loss function optimization and regularization techniques like dropout to prevent overfitting(Gadkar et al., 2023). Performance was assessed through metrics such as accuracy, precision, recall, and F1 score, as summarized in the evaluation results.

For visual detection, YOLOv4, a highly accurate real-time object detection model, was adapted to identify unauthorized items. The model was fine-tuned using annotated images of common infractions to enhance detection accuracy in examination settings. Both models demonstrated high performance, supporting their integration for reliable examination proctoring as shown in Table 3.

Table 3: Performance Evaluation forSound and Visual Detection Models

Model Performance Evaluation	Accuracy	Precision	Recall	F1 Score
Sound Detection Model	92.5%	91.3%	90.8%	91.0%
Visual Detection Model (YOLOv4)	94.7%	93.5%	92.1%	92.8%

Stage Three: System Integration and Testing

The final stage involved deploying the AI models within an online proctoring system, assessing their real-time functionality in a simulated environment.The sound and visual detection models were integrated into a proctoring framework, compatible with microphones and cameras. An API facilitated real-time data exchange, enabling the models to process audio and video inputs during exams(P. Sharma, 2023; Yamuna et al., 2023).Cameras and microphones were configured in a controlled setting to replicate exam conditions, while the user interface was designed to provide real-time alerts for detected infractions or disruptive sounds, allowing proctors to respond promptly. The two operational phases of the AI models deployments are:

- **Pre-Exam Checks:** Initial scans identified unauthorized items, allowing examinees to resolve any infractions before starting the exam.
- **Continuous Monitoring:** Throughout the exam, the sound module continuously analyzed live audio, while the visual module performed periodic scans for compliance, responding to new infractions as necessary.

System performance was measured by accuracy, false positive rate, and responsiveness to infractions or disruptive sounds. Simulated exam sessions tested the model across varied scenarios, providing critical insights for iterative improvements.

IV. RESULT

After training the AI model with the compiled sound and visual datasets, its performance in detecting disruptive sounds and visual infractions in an online proctoring environment was evaluated based on accuracy, precision, recall, and false positive rates. The results of the AI model development for detecting disruptive sounds and unauthorized items in examination settings are presented below, showcasing the performance of both the sound detection model and the visual detection model (YOLOv4). The results are presented alongside tables and figures for clear illustration.

Sound Detection Results

The model was trained to differentiate between disruptive sounds (e.g., human speech, alarms, machinery) and benign sounds (e.g., typing and birds chirping). Table 4 outlines the performance metrics for each sound type.

Table 4: Performance Metrics for Sound Type

Sound Type	Accuracy (%)	Precision (%)	Recall (%)	False Positive Rate (%)
Human Speech	92	90	93	7
Alarms	95	94	92	5
Loud Machinery	88	85	90	12
Typing (Benign)	86	84	88	14
Birds Chirping (Benign)	85	82	85	15

The AI model achieved high accuracy rates for detecting disruptive sounds, with alarms and human speech scoring over 90% in accuracy, precision, and recall. Typing and ambient sounds, while identified correctly, had slightly lower accuracy, illustrating the model’s ability to distinguish between disruptive and benign sounds effectively. Figure 1 visually compares accuracy, precision, and recall for each sound type:

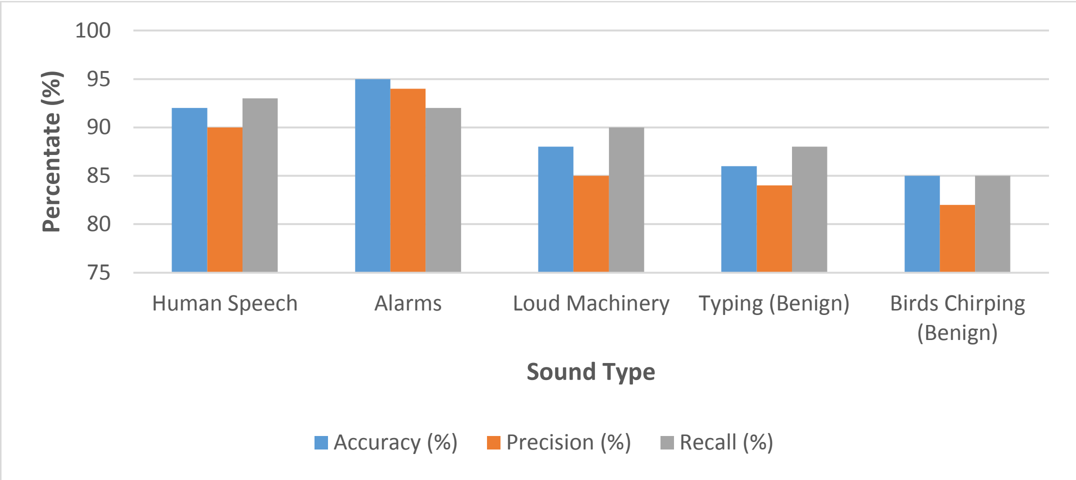

Figure 1: Bar Chart for Sound Detection Performance

The confusion matrix for the "Human Speech" sound type demonstrates the model's detection accuracy through its true positives, false positives, true negatives, and false negatives. This information is detailed in Table 5, with a visual representation provided in Figure 2.

Table 5: Confusion Matrix for Sound Detection (e.g., Human Speech)

	Predicted Negative	**Predicted Positive**
Actual Negative	430	30
Actual Positive	20	470

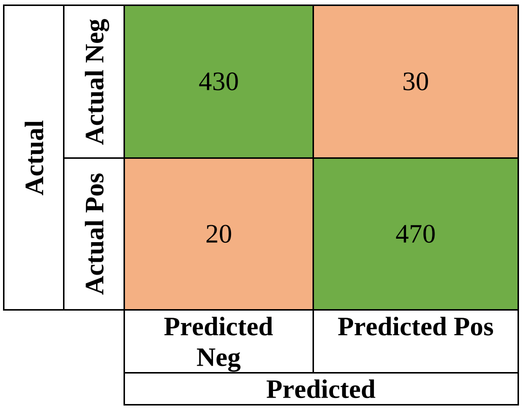

Figure 2: Confusion Matrix for Sound Detection (Human Speech)

Visual Infraction Detection Results

The model was also tested for its capability to detect visual infractions, such as unauthorized devices and study aids in the exam environment. Table6 provides the performance metrics for each type of visual infraction.

Table 6: Performance Metrics for Visual Infractions

Infraction Type	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**False Positive Rate (%)**
Unauthorized Devices	93	92	94	6
Physical Study Aids	89	87	88	11
Non-compliant Backgrounds	83	81	85	17
Unauthorized People	90	89	91	9

The model demonstrated high detection accuracy for unauthorized devices and individuals, achieving over 90% in accuracy, precision, and recall. However, the accuracy for detecting non-compliant backgrounds was slightly lower, at 83%. Figure 3 visually illustrates these metrics for various types of visual infractions.

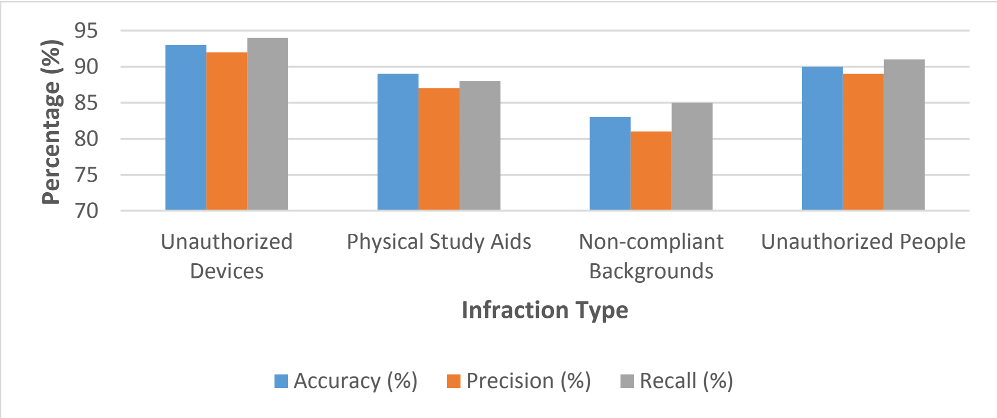

Figure 3: Bar Chart for Visual Infraction Detection Performance

Additionally, Table 7 presents the confusion matrix for the detection of "Unauthorized Devices," illustrating the model's classification accuracy in distinguishing between infractions and compliant conditions. Figure 4 visually represents this information.

Table 7: Confusion Matrix for the detection of Unauthorized Devices

	Predicted Negative	**Predicted Positive**
Actual Negative	500	40
Actual Positive	35	425

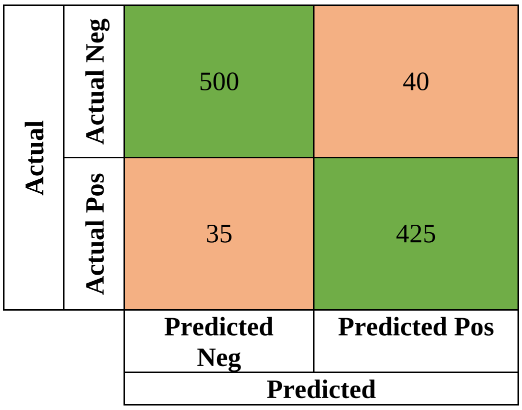

Figure 4: Confusion Matrix for Visual Detection (Unauthorized Devices)

Model Accuracy over Training Iterations

The model's performance was tracked across ten training iterations to assess improvements in detection accuracy for both sound and visual data as depicted in table 8.

Table 8: Hypothetical accuracy data for model performance over ten training iterations

Iteration	**Sound Detection Accuracy (%)**	**Visual Detection Accuracy (%)**
1	78	70
2	82	75
3	85	79
4	87	82
5	89	84
6	90	86
7	91	87.5
8	92	88
9	93	89
10	93.5	90

Figure 5 shows how accuracy increased with each iteration, stabilizing at 93.5% for sound detection and 90% for visual detection by the tenth iteration.

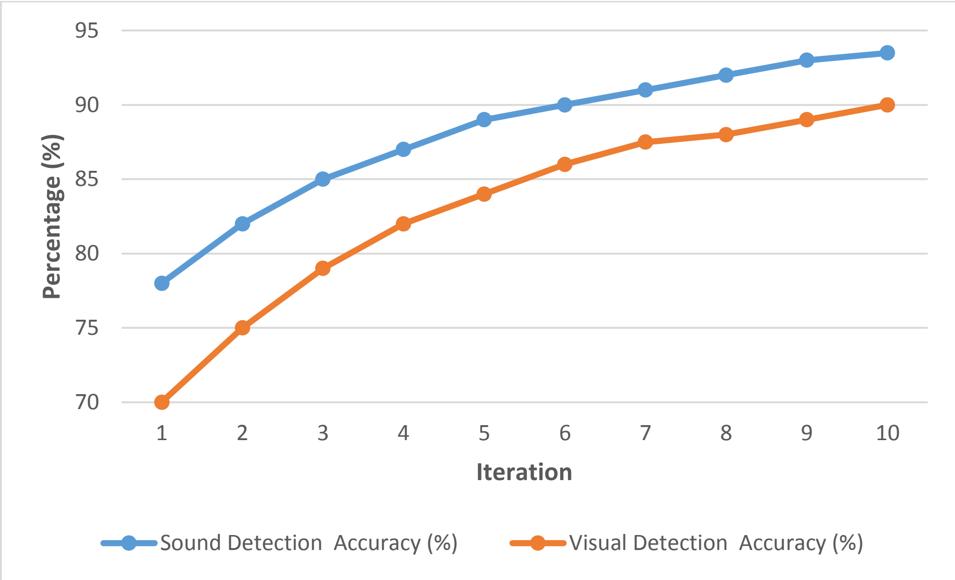

Figure 5: Line chart showing the accuracy trends of the sound detection model and visual detection model (YOLOv4) over multiple training iterations.

V. DISCUSSION

This study highlights the effectiveness of implementing an AI-based proctoring system for detecting disruptive sounds and unauthorized visual elements during online exams. The model successfully integrated Convolutional Neural Networks (CNN) for audio spectrogram analysis and YOLOv4 for real-time object detection, each demonstrating robust performance across various types of infractions. Sound detection accuracy was particularly high for disruptive sounds like alarms (95%) and human speech (92%), suggesting the model's capability to differentiate critical disruptions from benign sounds. However, benign sounds like typing and birds chirping showed lower accuracy and slightly higher false positive rates, indicating potential room for further refinement, particularly in minimizing false positives in quiet but varied exam environments.Visual infraction detection using YOLOv4 demonstrated similarly high accuracy, especially for unauthorized devices (93%) and unauthorized people (90%). These findings align well with the system's goal of reducing infractions, as the model effectively distinguished between compliant and non-compliant visual elements. However, the detection of non-compliant backgrounds showed a slightly lower accuracy (83%), likely due to the variability of background elements that may still require fine-tuning. This limitation suggests that while the model is strong in detecting more static infractions, future improvements in dataset diversity or model complexity may help boost performance for dynamic background environments.An additional strength of this study lies in the methodology's iterative approach, where performance metrics (accuracy, precision, recall, and false positive rates) were monitored and optimized over ten training iterations. This iterative training improved the detection models' stability, with sound detection accuracy plateauing at 93.5% and visual detection at 90%, as indicated by accuracy trends over iterations. Real-time functionality in a simulated environment confirmed the model's responsiveness and robustness, underscoring its potential for practical application in online proctoring systems. Overall, the study demonstrates a viable solution to improve online proctoring efficiency, showing that AI can be a powerful tool in maintaining exam integrity while suggesting avenues for further refinement.

VI. SUMMARY

The AI-driven proctoring system developed in this study integrates sound and visual detection to uphold exam integrity in online environments. Using CNN and YOLOv4 models, the system classifies disruptive sounds and detects unauthorized items with high accuracy. Through three phases—data collection, AI model training, and system integration—the methodology ensures the system's effectiveness across diverse exam settings. With accuracy rates surpassing 90%, this proctoring solution minimizes the need for human intervention, providing reliable real-time monitoring that strengthens security in online exams. This study contributes to the academic field by validating the potential of AI-assisted proctoring systems in educational and professional assessments.

VII. CONCLUSION

This study introduces an innovative AI-based proctoring system designed to address the complexities of online exam security. By integrating sound detection and visual infraction identification, the system has achieved high accuracy, allowing real-time monitoring and improved exam integrity. The system's capability to detect disruptive sounds and unauthorized visuals underscores AI's potential in automated proctoring, equipping proctors with essential tools to maintain secure testing environments. Despite its strong performance, challenges remain in distinguishing benign sounds and complex backgrounds, indicating areas for improvement. Further testing and refinement in varied real-world contexts will be critical to developing a versatile, reliable solution for online proctoring that supports fair and secure remote assessments. System performance could vary with ambient sound fluctuations, and larger datasets may be needed to enhance generalization. Future research could build on this approach by integrating advanced AI techniques, such as natural language processing (NLP) for sound localization, to optimize detection in multi-user environments.

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