

AI-DRIVEN REAL-TIME PROCTORING SYSTEM FOR ONLINE EXAMS USING COMPUTER VISION

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ABSTRACT

Concerns about the validity of remote exams have grown as a result of the quick growth of online learning. The methods of manual invigilation are not scalable, costly, and prone to errors. The AI-driven real-time proctoring system described in this study uses computer vision techniques to autonomously monitor examinee conduct during online exams. The system examines real-time webcam video streams to identify anomalous head movements, multiple people, missing faces, mismatched identities, and the use of forbidden objects like cell phones. Real-time alerts and comprehensive activity logs are produced by combining YOLO-based object detection models, head pose estimates, and deep learning-based face identification. The suggested solution is appropriate for large-scale online assessments since experimental findings show that it successfully

improves exam security while reducing human interaction.

KEY WORDS: *Online Proctoring, Computer Vision, Face Recognition, Head Pose Estimation, YOLO, Artificial Intelligence, Exam Security.*

INTRODUCTION

Concerns about the reliability of remote exams have grown due to the quick growth of online learning. Manual invigilation methods are costly, prone to errors, and not scalable. The AI-driven real-time proctoring system presented in this research uses computer vision techniques to autonomously monitor examinee conduct during online exams. The system examines live camera video streams to identify anomalous head movements, multiple people, the lack of faces, identity inconsistencies, and the use of forbidden objects like cell phones. Real-time alerts and comprehensive activity logs are

produced by integrating YOLO-based object detection models, head pose estimation, and deep learning-based face identification. The suggested technique is appropriate for large-scale online assessments since experimental observations show that it efficiently improves exam security while reducing human intervention.

LITERATURE REVIEW

Automated proctoring systems have been the subject of more recent study in order to guarantee the integrity of online exams. Face recognition methods are used in many studies to authenticate candidates both before and during exams. Examinee attention has been tracked and suspicious behavior has been identified using eye gaze tracking techniques. It has been shown that head position estimation is a useful tool for spotting unusual motions that might point to cheating. Algorithms for object detection are frequently used to identify forbidden objects, such cell phones. Because they can identify in real time, YOLO-based models are very well-liked. Certain systems depend on deep learning models, which demand a lot of processing power. Other methods rely on post-exam analysis and lack real-time monitoring. The detection reliability of

current systems is decreased by the limited integration of different behavioral markers. By integrating object detection and facial analysis into a single real-time framework, the suggested solution fills up these gaps.

RELATED WORK

AI-based methods for online exam proctoring have been investigated in a number of studies. Candidate authentication frequently makes use of face recognition technology. To track attention, head posture estimation and eye gaze tracking are used. During exams, object detection models assist in identifying items that are disallowed. In real-time detection tasks, YOLO-based detectors have proven to be highly accurate. Certain current systems need expensive or specialized hardware. Some merely pay attention to one behavioral indicator. Overall detection reliability is decreased by limited scope. Frequently, real-time monitoring is not completely integrated. By integrating several detection methods into a single framework, the suggested approach gets over these restrictions.

EXISTING METHOD

The majority of current online proctoring techniques rely on live video conferencing solutions for manual invigilation. During tests, candidates are observed by human supervisors using webcams. This method is expensive and challenging to expand to accommodate many pupils. Fatigue and subjective judgment errors are common among human invigilators. Some systems do not do real-time analysis; they just record webcams in a simple manner. Video review after an exam is ineffective and time-consuming. Some automated systems just use facial recognition to confirm their presence. Others do not do any behavioral analysis; they just monitor screens. Overall effectiveness is decreased when cheating indicators are not detected. These drawbacks emphasize the necessity of an intelligent automated proctoring system.

PROPOSED METHOD

The suggested approach presents a computer vision-based AI-powered real-time online proctoring system. The candidate's webcam is used by the system to continuously record live video. Face detection guarantees the examinee's continuous presence throughout the test. Candidate identification is confirmed by face recognition using registered data.

Abnormal head motions and attention loss are tracked by head pose estimation. Mobile phones and other forbidden goods are identified by YOLO-based object detection. The presence of several people in the picture is also detected by the system. Every moment suspicious activity is identified, real-time notifications are produced. For auditing purposes, timestamps are recorded for every event. Exam security is increased and human intervention is decreased using this automated method.

SYSTEM ARCHITECTURE

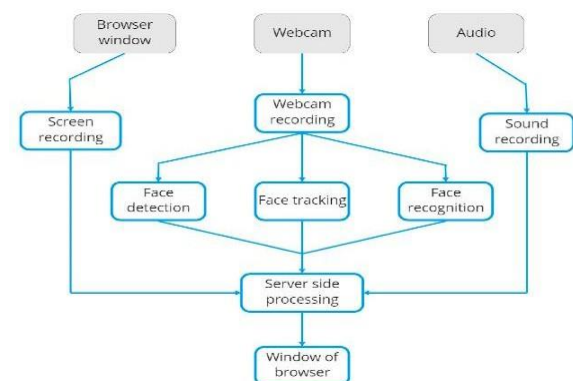


Fig 1: System Architecture

The suggested system is a Flask-based AI proctoring program that uses computer vision algorithms to evaluate real-time webcam video frames and identify instances of cheating.

METHODOLOGY DESCRIPTION

The system begins by verifying webcam availability and initiating video capture. Face detection ensures continuous presence of the candidate. Face recognition compares detected faces with registered identities. Unknown faces are immediately flagged as violations. Head pose estimation calculates yaw, pitch, and roll angles. Excessive head movement is treated as suspicious behavior. YOLO-based object detection scans the video frame continuously. Mobile phones and additional persons are detected automatically.

RESULTS AND DISCUSSION

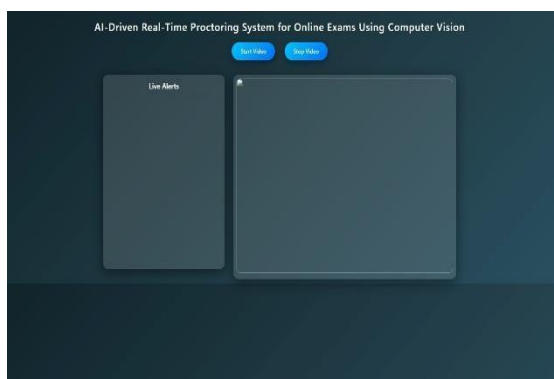


Fig 2: Home page



Fig 3: When the camera detects the user



Fig 4: When the unknown person detected.

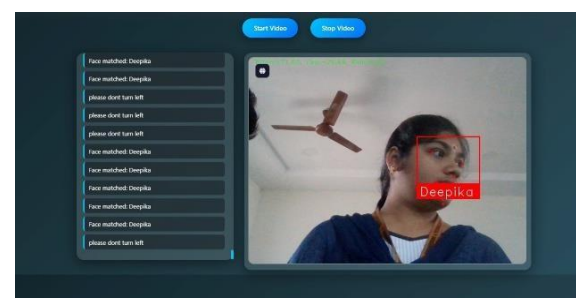


Fig 5: When the user turns left.



Fig6: When the user turns right.



Fig 7: When the camera detects the mobile.

CONCLUSION AND FUTURE ENHANCEMENT

This paper presents an AI-driven real-time online proctoring system. The system enhances exam security using computer vision techniques. Automated invigilation reduces reliance on human supervisors. Facial analysis ensures candidate authentication and presence. Head pose estimation helps detect inattentive behavior. Object detection prevents the use of prohibited items. The system demonstrates reliable real-time performance. Scalability makes it suitable for large-scale online exams. Future work includes integrating audio-based cheating detection. Additional enhancements may involve cloud deployment and emotion analysis.

REFERENCES:

- [1] Harini, P. (2019). GESTURE CONTROLLED GLOVES FOR GAMING AND POWER POINT PRESENTATION CONTROL. *GESTURE*, 6(12).
- [2] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You Only Look Once: Unified, real-time object detection," *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, pp. 779–788, 2016.
- [3] J. Redmon and A. Farhadi, "YOLOv3: An incremental improvement," arXiv preprint arXiv:1804.02767, 2018.
- [4] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," *Adv. Neural Inf. Process. Syst.*, vol. 25, pp. 1097–1105, 2012.
- [5] O. M. Parkhi, A. Vedaldi, and A. Zisserman, "Deep face recognition," *Proc. Brit. Mach. Vis. Conf. (BMVC)*, pp. 1–12, 2015.
- [6] F. Schroff, D. Kalenichenko, and J. Philbin, "FaceNet: A unified embedding for face recognition and clustering," *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, pp. 815–823, 2015.
- [7] T. Baltrusaitis, P. Robinson, and L.-P. Morency, "OpenFace: An open source facial behavior analysis toolkit," *Proc. IEEE Winter Conf. Appl. Comput. Vis. (WACV)*, pp. 1–10, 2016.
- [8] V. Kazemi and J. Sullivan, "One millisecond face alignment with an ensemble of regression trees," *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, pp. 1867–1874, 2014.
- [9] Z. Zhang, "A flexible new technique for camera calibration," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 22, no. 11, pp. 1330–1334, 2000.

- [10] D. Lowe, "Distinctive image features from scale-invariant keypoints," *Int. J. Comput. Vis.*, vol. 60, no. 2, pp. 91–110, 2004.
- [11] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards real-time object detection with region proposal networks," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 39, no. 6, pp. 1137–1149, 2017.
- [12] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *Int. Conf. Learn. Representations (ICLR)*, 2015.
- [13] M. Turk and A. Pentland, "Eigenfaces for recognition," *J. Cogn. Neurosci.*, vol. 3, no. 1, pp. 71–86, 1991.
- [14] H. Wang and L. Wang, "Beyond triplet loss: A deep quadruplet network for person re-identification," *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, pp. 403–412, 2017.
- [15] P. Viola and M. Jones, "Rapid object detection using a boosted cascade of simple features," *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, pp. 511–518, 2001.
- [16] A. Rosebrock, *Deep Learning for Computer Vision with Python*, PyImageSearch, 2017.
- [17] N. Dalal and B. Triggs, "Histograms of oriented gradients for human detection," *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, pp. 886–893, 2005.
- [18] M. Abadi et al., "TensorFlow: A system for large-scale machine learning," *Proc. 12th USENIX Symp. Oper. Syst. Des. Implement.*, pp. 265–283, 2016.
- [19] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.
- [20] C. Szegedy et al., "Going deeper with convolutions," *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, pp. 1–9, 2015.