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REAL-TIME MALPRACTICE DETECTION IN EXAM HALLS BY ENFORCING MINIMUM DISTANCE SEATING ARRANGEMENT USING YOLO

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Abstract : Academic dishonesty which includes malpractice and plagiarism, is a major issue in educational institutions worldwide and is particularly prevalent in entrance exams, certification exams, and university exams. Traditional methods of detecting malpractice such as manual monitoring by invigilators, are often inadequate and can be time-consuming and expensive. In this paper, we present a malpractice detection system for use in exam halls that leverages machine learning algorithms and computer vision libraries to detect instances of malpractice and other forms of academic dishonesty. The system uses video monitoring to identify suspicious behavior by test takers. Our system gives us the possibility to enhance the integrity of high-stakes exams and maintain a level playing field for all test subjects by automatically detecting malpractice in exam rooms.
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***IndexTerms* - bounding boxes, deep learning, malpractice, object detection, twilio, YOLOv5.**

I. INTRODUCTION

Malpractice poses a serious threat to the integrity of exams and the credibility of academic qualifications. One of the most frequent kinds of malpractice during a test is copying from other students, using unapproved materials or seeking assistance from external sources. A malpractice detection system is one of the solutions being developed in recent years to identify and stop cheating in exam rooms. The primary focus of a video surveillance system is to extract video sequences and then analyze the obtained information for any suspicious activities if involved. Nowadays, students are adapting different techniques involved in malpractice during the course of an examination. A malpractice detection system is a computer-based tool that uses a range of techniques to monitor and analyze the behavior of exam takers in real-time, with the aim of detecting any signs of cheating or other forms of malpractice. This system typically relies on a combination of video surveillance, audio monitoring, and data analytics to identify suspicious patterns of behavior, such as repeated glances at unauthorized materials, unusual movements, or communication with other individuals. Upon detection of such practices, the system will alert examiners or administrators who can take appropriate measures to avoid further irregularities. The development of a malpractice detection system possesses the potential to significantly enhance the fairness and reliability of exams, by providing a more objective and efficient means of detecting malpractice in examinations

II. LITERATURE REVIEW

Examination all over the world is the basic tool for assessing the competency and capabilities of individuals in every educational system. Yew et al. proposed a technique that uses the video frame from the camera as input and an open-source pre-trained object detection model according to the YOLOv3 algorithm to detect pedestrians. To be able to use a two-dimensional plane for distance calculation, the video footage is then transformed into top-down view. The approach described by Alexey et al. uses a state-of-the-art detector called the MS COCO AP50...95 and AP50, which is faster in terms of FPS and more accurate than all other existing alternative detectors. There are several characteristics that are reported to increase Convolutional Neural Network (CNN) accuracy, making it possible to train and utilize the detector described on a typical GPU with 8–16 GB-VRAM, which allows for its widespread usage. A current detector consists of two parts: a head that predicts classes and bounding boxes and a backbone that is pre-trained on ImageNet. When comparing similar performance, YOLOv4 runs twice as quickly as Efficient Det. increases the AP and FPS of YOLOuv3 by 10% and 12%, respectively. A social distance monitoring approach for COVID-19 has been provided by Imran et al. Pre-trained YOLOv3 paradigm is utilized for person detection. The transfer learning approach is utilized to enhance the model's performance since the human characteristics seem quite different from the above perspective. The old model is supplemented by the newly trained layer. To identify those who approach too closely and breach or violate social distances, an algorithm is utilized. A deep learning-based approach was suggested by Narinder et al. to facilitate the automation of using surveillance video to monitor the epidemic. This method makes use of two deep learning algorithms called YOLOv3 and Deepsort to identify and track individuals at the same time via security cameras. The YOLOv3 method is utilized to locate and identify people in camera photos, while Deepsort is utilized to follow people over time and measure their distances from one another. In comparison to the prior best outcome on VOC 2012, Ross et al. provided a model for a straightforward and scalable detection technique that leads to an increase in mean average precision (mAP) by more than

30%. As a consequence of mixing CNNs with regional proposals, it's called RCNN. To obtain characteristics that can be utilized for distinguishing objects of different sizes and orientations, the authors have suggested that CNNs are trained on photographs. To increase the efficiency and precision of such identification, Wang et al. suggested a deep learning tiny object-detection approach based on picture super-resolution. Small-object identification is essential for a variety of tasks, including finding pedestrians or traffic signals that are nearly undetectable in low-resolution photos. According to the study of linked studies done above, the majority of researchers employed the YOLO algorithm to identify social alienation during the COVID-19 epidemic. In the area of effective examination invigilation, our main objective is to develop a malpractice detection method using YOLOv5. Adopting YOLOv5 has a number of benefits over earlier versions, including being quicker and more accurate. On the COCO dataset, it achieves cutting-edge results while being up to 4x faster than YOLOv4. In comparison to earlier iterations, YOLOv5 has a novel architecture that is both more effective and simpler to train. It is simple to scale to various objects and image sizes.

III. METHODOLOGY

Initially, the live video is processed through the surveillance camera, embedded into the system and then each frame is extracted from the video and analyzed for further actions. The procedure involved is depicted in Figure 1. The malpractice detection system is made up of three main components: video data acquisition, object detection, and alert generation. Video data acquisition is used to gather video recordings from surveillance cameras in the examination rooms. To be able to detect humans, object detection uses several sophisticated deep learning algorithms. The distance between people is calculated after they have been detected. If the required distance is not met, an alert generation component shall send alerts by means of SMS. There are various modules used which are namely the authentication module, video feed capture module, object detection module, distance calculation module and SMS alert module.

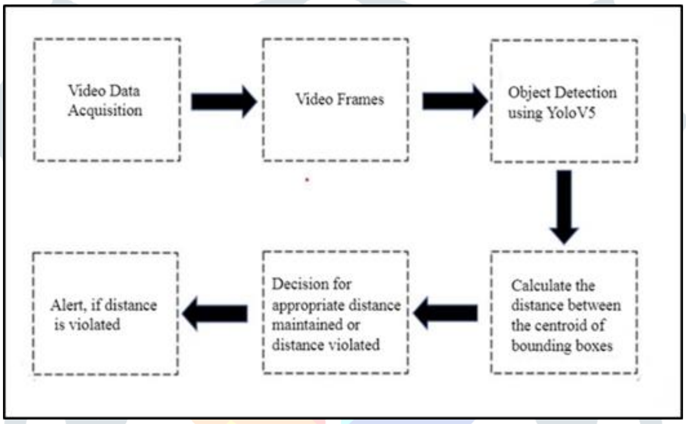

Fig 1 Architectural Design

To ensure that only approved and authorized users have access to the video and audio feeds, an authentication module is responsible. That is intended to provide security, avoid unauthorized access and protect sensitive information. The capture of video feed originating from a camera or another source shall be undertaken by the video feed capture module. In real-time, it interfaces with the video source and retrieves the picture frames. To capture video frames from a video source, this module uses the OpenCV library. Next, the captured frames are received by the object detection module for further processing. The malpractice detection system takes input from this system. The object detection module uses YOLOv5, a state-of-art deep learning algorithm, to detect people in the video feed. An algorithm is trained to generate a list of bounding boxes for each person in the frame, based on a large set of images. Using PyTorch's training capabilities, the module for detecting objects is trained on a large set of labeled images. This information is transmitted to the distance calculation module that calculates the distances between persons in the frame after the object detection module has created list of bounding boxes. The module calculates the distance between all pairs of bounding boxes in the frame and checks if the distance is less than 1.5 meters which is the minimum required distance. If the distance is less than a certain threshold or the required distance, an alert is generated to notify the authorities. The output is a list of the distance between each pair of people in that frame. The Twilio package will be used for sending SMS alerts when a suitable distance is not maintained in the SMS alert module. The responsibility for monitoring and determination of whether they maintain a safe distance lies with this module. The Twilio API will generate and send an SMS alert to the specified list of phone numbers if the distance is below a certain threshold. It requires a Twilio account and an authentication token to access the Twilio API. The phone numbers of the recipients who should receive the alerts are also defined in the module. When an alert is generated, the message is constructed with the relevant information, such as the location and time of the violation, and sent to the recipients' phones.

IV. EXPERIMENTAL RESULTS

Figure 2 shows the snapshot of the login page. This login is used to request the credentials of the user and helps to secure them as it provides access to only authorized users. Figure 3 is a frame extracted from the video feed for further analysis. It shows the image objects detected in the frame. The detected objects are labelled as person. It uses a deep learning algorithm

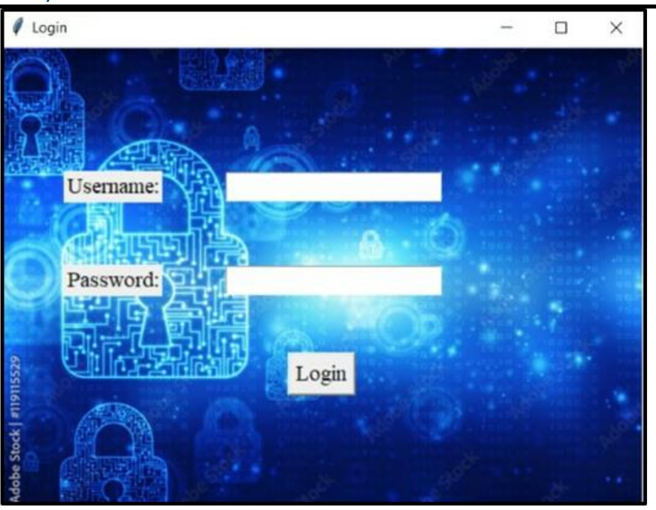

Fig 2 Snapshot of Login Page

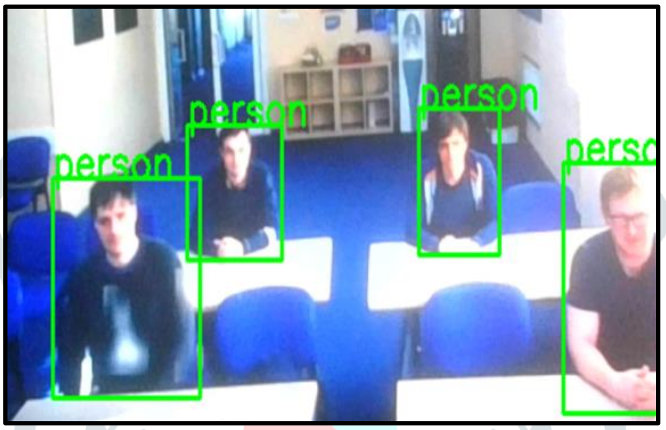

Fig 3 Snapshot of Detection of Objects

YOLOv5, for detecting objects which are people in the video feed. This generates list of bounding boxes for each person in the frame. This information is passed to the distance calculation module, for calculating the distance between people in the frame. The distance calculated between pairs of bounding boxes is found using the distance calculation module. The Euclidean distance formula is used for calculating the distance between the center points of the bounding boxes. It checks if the distance calculated is less than the minimum required distance of 1.5 meters. Figure 4 shows the snapshot of malpractice detection when

Fig 4 Snapshot of Malpractice detection

appropriate distance is not maintained and an alert message is displayed on the screen. The time when malpractice is detected is included in the alert message. If the distance is less than the required distance, an alert is sent to notify the users. In the SMS alert module, the Twilio package is used to send SMS alerts when the required distance is not maintained. If the distance is less than certain threshold, an SMS alert is generated and sent to a predefined list of phone numbers using Twilio API. The phone numbers of recipients who should receive the alerts are also defined in the module.

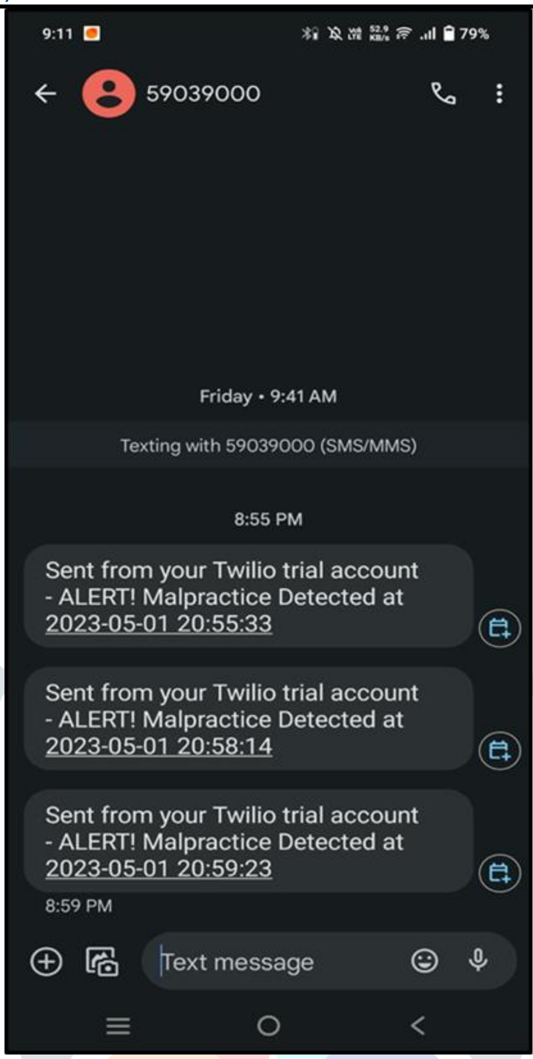

Fig 5 Snapshot of the alert messages

Figure 5 shows the alert message constructed with information such as the location and time of the violation and malpractice detection, which is sent to the recipients' phones.

V. CONCLUSION AND FUTURE SCOPE

In this paper, a YOLOv5-based malpractice detection system has been proposed to detect malpractice in exam halls. This system uses advanced technologies such as computer vision and machine learning to detect potential instances of cheating, which can be immediately flagged and reported to the exam authorities. The system detects objects and creates bounding boxes. The distance is calculated between bounding boxes and alerts are sent if the minimum threshold is not maintained. This system can be further improvised by adding capabilities such as e-mails sent to the authorities. Graphs could be added for further analysis in the education sector. The other areas of development include biometrics and blockchain. Biometrics can help to avoid impersonation and blockchain helps in storing exam data in a secure manner.

REFERENCES

[1] Yew Cheong Hou, Mohd Zafri Baharuddin, Salman Yussof, and Sumayyah Dzulkifly. Dec 2020. "Social Distancing Detection with Deep Learning Model". IEEE Access

[2] Alexey Bochkovskiy. April 2020. "YOLOv4: Optimal Speed and Accuracy of Object Detection". Chien-Yao Wang Institute of Information Science Academia Sinica, Taiwan, Hong-Yuan Mark Liao Institute of Information Science Academia Sinica, Taiwan.

[3] Imran Ahmed, Misbah Ahmad, Joel J.P.C. Rodrigues, Gwanggil Jeon, and Sadia Din. Nov 2020. "A deep learning-based social distance monitoring framework for COVID-19". Elsevier

[4] Narinder Singh Punn, Sanjay Kumar Sonbhadra, Sonali Agarwal, and Gaurav Rai. April 2021. "Monitoring COVID-19 social distancing with person detection and tracking via fine-tuned YOLO v3 and Deepsort techniques".

[5] Ross Girshick, Jeff Donahue, Trevor Darrell, and Jitendra Malik. 2014. "Rich feature hierarchies for accurate object detection and semantic segmentation". IEEE

[6] Zhuang-Zhuang Wang, Kai Xie, Xin-Yu Zhang, Hua-Quan Chen, Chang Wen, and Jian-Biao He. April 2021. "Small-Object Detection Based on YOLO and Dense Block via Image Super-Resolution". IEEE Access, Vol 9

[7] A. Y. Abdul Kareem, A. T. Alabi. 2004. "Curbing Examination Malpractice in the University system". Nigerian Journal of Educational Research and Evaluation, Vol. 5, No. 1

[8] B. C. Amanze, C. C. Ononiwu, B. C. Nwoke, I. A. Amaefule. January 2016. "Video Surveillance And Monitoring System For Examination Malpractice In Tertiary Institutions". International Journal Of Engineering And Computer Science, Vol. 5, pp. 15560-15571.

[9] G. Sandhya Devi, P. G. V. D Prasad, G. Suvarna Kumar, V. Chaitanya. 2015. “A Mono Master Shrug Matching Algorithm for Examination Surveillance”. I.J. Information Technology and Computer Science, 01, pp. 81-86 vol. 1.

[10] Ahad, M.A.R. 2011. “Computer vision and action recognition: a guide for image processing and computer vision community for action understanding”.

[11] D.T. Nguyen, W. Li, P.O. Ogunbona. 2016. “Human detection from images and videos: A survey”. Pattern Recognition, 51:148-75.

[12] A. Krizhevsky, I. Sutskever, G.E. Hinton. 2012. “Imagenet classification with deep convolutional neural networks”. In Advances in neural information processing systems, pp. 1097- 1105.

[13] J. Redmon, S. Divvala, R. Girshick, A. Farhadi. 2016. “You only look once: Unified, real-time object detection”. In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 779-788.

[14] T. Dean, M. A. Ruzon, M. Segal, J. Shlens, S. Vijayanarasimhan, and J. Yagnik. 2013. “Fast, accurate detection of 100,000 object classes on a single machine”. In CVPR.

[15] J. Donahue, Y. Jia, O. Vinyals, J. Hoffman, N. Zhang, E. Tzeng, and T. Darrell. 2014. DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition. In ICML.