Journal of Information Systems Engineering and Management
2025, 10(33s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Object Detection for Real-Time Malpractice Detection in Classrooms Using Computer Vision

Shruti Maria Shibu[1], Dea Elizabeth Varghese[2], Divya James[3], Noel Mathen Eldho[4], Allen Prince[5]
[1,2,4,5]Department of Computer Science and Business Systems, Rajagiri School of Engineering & Technology, Kochi, Kerala, India
sshrutishibu@gmail.com, deaeliz@gmail.com, noelmathen03@gmail.com, prince.allen1820@gmail.com
[3] Associate Professor, Department of Computer Science and Business Systems, Rajagiri School of Engineering & Technology, Kochi, Kerala, India
divyaj@rajagiritech.edu.in

ARTICLE INFO

Received: 18 Dec 2024

Revised: 10 Feb 2025

Accepted: 28 Feb 2025

ABSTRACT

Ensuring academic integrity during examinations requires timely and effective detection of unauthorized items and suspicious behaviors. This project focuses on the object detection module within a larger system designed to identify students, invigilators, and prohibited items, such as mobile phones and notes, in classroom environments. A comparative analysis of detection models, including YOLOv8, YOLOv11, Fast R-CNN, and SSD, was conducted to evaluate key metrics. The results of different experiments revealed that YOLOv8 was the most successful model because of its high accuracy, occlusion-handling ability, and real-time processing capabilities. YOLOv8 performed better in real-world classroom scenarios by striking the ideal mix between speed and accuracy, making it a dependable option for object detection in dynamic environments. These results use YOLOv8's potential as the core component of a comprehensive system for real-time malpractice detection, ushering in integrity and fairness in exams. By having such advanced object identification methods embedded within monitoring systems, this approach ensures morality in AI-based solutions that emphasize equity and accountability in education.

Keywords: Malpractice detection; YOLOv8; Examination surveillance; Real-time object detection; Academic misconduct prevention.

INTRODUCTION

Object detection refers to a basic application of computer vision that identifies and pinpoints possibly several object categories appearing in images or video frames. This has gained traction across various fields such as autonomous vehicles, health monitors, and surveillance systems, and its application in an educational context has demonstrated significant promise. Advances in Deep Learning have brought forth highly efficient object detection models, including YOLO (You Only Look Once), SSD (Single Shot Detector), and Faster R-CNN (Region- Based Convolutional Neural Networks); of these YOLOv8 presents a very strong solution for real-time applications combined with lightweight architecture and good detection performance.

The proposed system focuses on accurately detecting teachers and students-an essential prerequisite for developing a full-fledged system to detect prohibited activities and behaviors during examinations. Using the real-time capabilities of YOLOv8 has fortified the model for operating under complex conditions in a classroom setting characterized by occlusions, light, and seating arrangements. This identification passes on to newer phases such as behavior analysis and anomaly detection, as they make it easier to audit exams via a straight assessment.

Classroom settings impose some unique challenges to object detection because the conversations and interactions one may have been dynamic, continuous overlaps between the individuals, and variation in the environment itself. This study addresses those challenges by constraining the detection task to two classes: students and teachers, thereby improving detection accuracy and system efficiency.

In order to train and evaluate the models under various conditions, a custom dataset consisting of classroom scenarios created just for this purpose was developed. After the system effectiveness was assessed, several object-detection models- such as YOLOTV8, YOLOT11, SSD, and Fast R-CNN were compared using metrics like precision,

Journal of Information Systems Engineering and Management
2025, 10(33s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

recall, and F1 score; and it was seen that YOLOT8 was superior to other models based on the real-time accuracy and adaptability making it more suitable for classroom-based applications. Additionally, the large scale and offline capability of systems make them usable in most educational institutions irrespective of constraints in resources.

On the basis of this, therefore, the proposed study validates object detection as the first layer of a strong AI-powered examination monitoring system and is focused on the proper identification of teachers and students. This work also contributes toward the operations concerning an efficient, scalable system designed for the future for upholding integrity in academics.

LITERATURE REVIEW

Dang et al. (2024) suggest a two-stage pipeline for student behavior recognition in classroom scenes by integrating object detection and image classification. Their approach effectively handles occlusion and scale variations by using a Shallow Auxiliary Module and a Vision Transformer (ViT). The overall mAP of 88.03 demands a much deeper cascading approach, which inherently increases the computational complexity and is challenging for the real-time deployment requirement. Their approach is less efficient for real-time applications compared to YOLOv8 since it does not provide end-to-end detection with lower latency. However, their feature extraction techniques could improve YOLO-based models suited for behavior analysis in educational settings.

Aziz et al. (2020) present a major review of deep- learning based object detection by discussing around 300 publications for various architectures, strategies, applications, and the current trends. The paper provides insight into the evolution of object detection models with respect to improvements and challenges in the field. However, since it was published in 2020, the review does not contain developments in newer models such as YOLOv8. Thus, though the survey provides a good foundation to understand object detection up until that point, it does not discuss the more recent methodologies and performance benchmarks pertinent to current research.

Liu et al. (2024) propose "YOLOv8n_BT," which enhances the YOLOv8n model by incorporating a Bi-Level Routing Attention (BRA) mechanism and a Tiny Object Detection Layer (TODL). These enhancements address the small object detection and occlusion problems, which are typical in classroom behavior recognition. The experimental results have demonstrated that the YOLOv8n_BT has precision, recall, F1 score, and mAP better than the baseline model - YOLOv8n. This can be translated to mean it is robust enough to overcome the challenges that occur in the classroom environment.

Xu et al. (2023) present a hybrid model that integrates gaze tracking and object detection to monitor student attention during classroom teaching. The model does not require the use of wearable devices. It is a non- intrusive tracking of student engagement in classrooms. However, this approach has some concerning possibilities with regard to privacy because of its use of visual data. Environmental factors such as lighting might also affect the accuracy of the system. An evaluation of the approach in different classroom environments will be needed to quantify its strength for presence in the classroom with different student activities and classroom interactions.

Ren, Zhang, and Li (2023) enhanced YOLOv5 for vehicle-mounted cameras to achieve real-time object detection. Their design allows room for motion blurring and target scale changes, which are essential in vehicular environments. The proposed model is strong for vehicular environments, but its direct application to classroom detection is very limited because of differences in dynamics and additional challenges. Even then the adapted techniques such as overcoming motion blur can be used to influence tailoring and adaptation for classroom use, especially for real-time detection in challenging environments.

Wang et al. (2024) introduce YOLOv10, the next- generation object detection framework that eliminates NMS in post-processing, reducing inference latency. Comprehensive experiments show that YOLOv10 achieves excellent performance in optimizing both accuracy and efficiency. One weakness of the research is that there is no analysis on the performance of YOLOv10 in concrete situations such as classroom object detection. More research into its application in classroom learning contexts will be needed to determine its suitability for real-time classroom monitoring.

Hussain et al. (2024) reviews the development of YOLO system from its version 5, 8, through 10 in this paper by analyzing their architectural advancement along with their performance. However, despite its importance it lacks

Journal of Information Systems Engineering and Management
2025, 10(33s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

empirical evaluation and comparison with other detection frameworks which might weaken it further when trying to find experimental data while dealing with further research. It does a solid job summarizing the YOLO models and makes an excellent reference source to appreciate what is achieved within the state-of-the-art real-time object detection.

Zhou et al. (2024) proposed the dual-path network DPNet specifically for light attention mechanisms applied in real-time object detection. The model caught high-level semantic features and low-level details of the object, and in that way optimized performance in environments with limited capabilities. Although DPNet is well-balanced in terms of accuracy and efficiency, its performance metrics—the 30.5% Average Precision (AP) on MS COCO — worse than the state-of- the-art models such as YOLOv8. However, DPNet is more versatile for applications with less computing power: real-time classroom behavior recognition.

Wang et al. (2023) proposed Gold-YOLO, which is a model that has added a Gather-and-Distribute (GD) mechanism to enhance multi-scale feature fusion. This enhances the mechanism to detect objects of various scales, thus improving the model's performance. Although the Gold-YOLO-N model seems to outperform YOLOv6-3.0-N on mAP, it might add extra computational complexity in real- time performance in classroom environments. However, the direction that the mechanism of GD seems to evoke seems promising in boosting object detection models even if they require the involvement of multi-scale feature fusion in other applications.

Shaikh et al. (2023) proposed an improved architecture of YOLOv5-7S optimized for real-time detection of multiple objects in Full HD videos. The authors enhance feature extraction through addition to the backbone through the addition of one extra layer and increase multi-GPU processing to process the Full HD videos in an efficient manner. This proposed model achieves better speed and accuracy, making it extremely apt for applications where real- time processing of high-resolution video streams is essential. Its application to classroom behavior analysis, specifically in high-definition video scenarios, may enhance the detection of other student behaviors.

Tan et al. (2020) proposed a compound scaling method and weighted bi-directional feature pyramid network. EfficientDet outperforms all other detectors in this case, with fewer parameters compared to the ones used before, but its dependence on compound scaling may make it inflexible or unable to adapt to some specific constraints on available resources. Also, its computational efficiency is not likely at par with that of YOLOv8, which was designed purely for real-time applications. Efficiency in terms of accuracy and scalability make it suitable for resource-constrained scenarios but may not be the best fit for classroom behavior recognition, which requires real-time detection capabilities.

Terven et al. (2023) proposed an excellent overview of the YOLO framework from YOLOv1 to YOLOv8 that describes how architectures and training approaches changed. The paper deals with the evolution of network architectures and training methodologies through different iterations of YOLO. This paper doesn't present novel experimental results. Therefore, it is not very useful for the researcher seeking empirical comparisons. Even though this is the case, it is an important work for a deeper understanding of the origin of YOLO and its role in real-time object detection.

Li et al. (2020) Generalized Focal Loss introduced a technique recently devised to improve dense object detection by generalizing the way the quality of classification and localization can be integrated into one single representation. The method outperforms the previous techniques on the COCO dataset because it offers better object detection, through more accurate bounding box localization, for uncertain cases. Although the GFL method offers significant improvements, a relatively complicated loss function significantly increases its computational overhead compared to a relatively simpler model like YOLOv8. Nonetheless, GFL's solution to inconsistency issues between training and the inference phase is promising enough in terms of enhancing object detection performance in classroom behavior recognition.

Guo et al. (2024) proposed a lightweight YOLOv8 model integrated with FasterNet for real-time underwater object detection. The integration reduces computational demands while maintaining high performance. Modifications to the bi-directional feature pyramid network further optimize the model for real-time detection. Although the study focuses on underwater environments, the techniques introduced could be adapted for classroom behavior

Journal of Information Systems Engineering and Management
2025, 10(33s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

recognition, particularly in constrained computational settings. The modified YOLOv8 is lightweight in design and has real-time processing capabilities, making it a good candidate for classroom monitoring systems.

Zhao et al. (2023) proposed BiTNet, a lightweight object detection network for real-time classroom behavior recognition. The model integrates a Transformer with a Bi-Directional Pyramid Network (BiPN) to enhance feature extraction and contextual understanding. BiTNet mainly does well in classifying classroom behaviors with mAP at 91.2% on the Classroom Behavior Recognition dataset. Though not compared directly with other state-of- the-art models like YOLOv8, its performance regarding it can also not be determined. The practical deployment of the model regarding its computational efficiency for real-time applications in classrooms also doesn't seem to be clear, hence further exploration is also worth developing.

PROPOSED METHODOLOGY

The proposed approach for the object detection module follows a structured workflow aimed at developing and evaluating models for identifying students and teachers in examination environments. It begins with the collection of a wide and diverse dataset, which includes the SCB dataset and footage from examination halls, which is then annotated to label key classes, such as the student and teacher.
Object detection has been performed through models such as YOLOv8, YOLOv11, SSD and FastRCNN. Videos of pre-recorded halls collected from examination footage from the college were prepared as test data. All these videos ran on the already trained models with the intention of running object detection along with class classification in each frame. Thus, identified objects are further elaborated to determine whether it is associated with a teacher or a student.

Finally, the models are evaluated using performance metrics, Precision, Recall, and F1 Score, which quantify the performance and reliability of the models. A systematic approach would thus lead to a well-defined and reproducible framework to meet the objectives of the research.

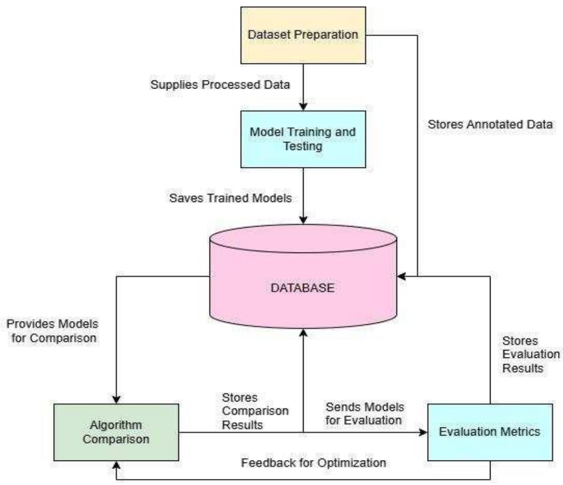

Figure. 1 Proposed Methodology

PERFORMANCE ANALYSIS

The malpractice detection system highlights object detection, and it aims to achieve real-time accuracy and efficiency in the detection of teachers and students in a classroom. The performance of four top- ranking object detection models was evaluated, which included YOLOv8, YOLOv11, Fast R-CNN, and SSD, considering performance metrics like precision, recall, F1 score, speed, and adaptability. The evaluation results validated the YOLOv8 model as the best candidate for the specific application- which is, for real-time detection within a classroom.

4.1 Experimental Setup:

The experiments were carried out on a system configured with the specified hardware and software requirements:

4.1.1. Hardware:

NVIDIA RTX 3050Ti GPU, Intel i7-12th Gen CPU, 16GB RAM

Journal of Information Systems Engineering and Management
2025, 10(33s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

4.1.2. Software:

Python 3.11, PyTorch 2.1.0, TensorFlow 2.14, YOLOv8 framework

4.1.3. Dataset:

The SCB dataset was simplified as different classes related to student behaviors, like "writing" and "reading", were merged together into a common "student" class while leaving "teacher" as a distinctive label. Thus, the detection task was actually much reduced by considering general identification of a student and of a teacher without focusing on precise behaviors. Meanwhile, the diversification within a "student" class was higher, thus also allowing for better generalization. The final dataset had 9,275 training images and 2,984 validation images to ensure a balanced representation and robustness for dynamic classroom environments.

4.2 Model Performance Metrics

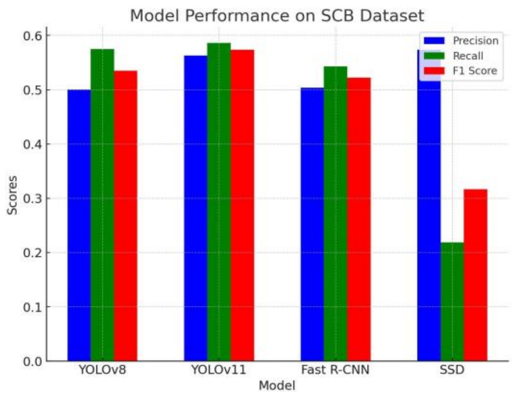

Figure. 2 Model Performance on SCB Dataset

Model	Precision	Recall	F1 Score
YOLOv8	0.5005	0.5751	0.5352
YOLOv11	0.5629	0.5862	0.5734
Fast R-CNN	0.5034	0.5432	0.5226
SSD	0.5734	0.2185	0.3164

Table. 1 Model Performance on SCB Dataset

To evaluate the models, key performance metrics that is Precision, Recall, and F1 Score were used, for analyzing object detection models in scenarios where high accuracy and low latency are essential. The performance of YOLOv8n, SSD, and Fast R-CNN is summarized in Figure 2.

4.3 Comparative Analysis

While comparing Fast R-CNN, SSD, YOLOv8n, and YOLOv11n, we can see that the YOLOv8n model is the most efficient. It is slightly better than the other object detection models, with its precision and recall being 0.5005 and 0.5751, respectively. Due to its lower latency and high precision, in real-time applications, the YOLOv8n emerges as an attractive option in primarily outperforming other explored models including Fast R-CNN and SSD models. The YOLOv11n on the other hand scored a very competitive mean average precision (mAP) at 0.5 of 0.582. Although impressive, its slow inference speed restricted it for real- time applications. For the surveillance task, SSD scored quite well in speed, though it does suffer from inaccuracy when it comes to figuring out more complex cases. Fast R-CNN is slow but good for an offline approach.

Ability to generalize across diverse classrooms was an important factor considered in evaluating the adaptability of the models. SCB datasets allowed both YOLOv8n and the YOLOv11n to work well among various lighting

Journal of Information Systems Engineering and Management
2025, 10(33s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

conditions, occlusions, and seating geometries. While SSD and Fast R-CNN proved less effective due to their lower adaptability issues, they tend to struggle with objects that were unclearly occluded or very modest changes in classroom behavior.

In real world applications, YOLOv8n consistently outperformed all models in terms of accurate and timely detection of objects. YOLOv11n performs significantly more efficiently within controlled environments than SSD or Fast R-CNN; however, a very slow inference speed limits its practicality within real-time scenarios. SSD was low performing due to the lack of speed it exhibited for real- time processing, specially in case of smaller object identification.

The decision to select YOLOv8n as the optimal model was further supported by its superior ability to generalize to unseen scenarios. Although theoretically, YOLOv11n performed better since it had a theoretical mAP@0.5 of 0.582 compared to YOLOv8n's 0.541, practical tests revealed that YOLOv8n generally delivered better qualitative results on detection accuracy and robustness. Its less complex architecture must have been at play here, allowing it to handle occlusions and dynamic variations effectively, as depicted in Figure 11. These strengths firmly placed YOLOv8n as the most suitable model for real- time exam monitoring.

RESULTS AND DISCUSSIONS

5.1. YOLOv8n Results

5.1.1. Training and Validation Performance:

The training process of YOLOv8n was conducted for 50 epochs, and the following metrics were captured:

5.1.2. Loss Curves:

Training and Validation Loss: The curves (refer to Figure 3) show a consistent decrease in the training loss across epochs, with validation loss stabilizing at around epoch 40. This indicates effective convergence and minimal overfitting.

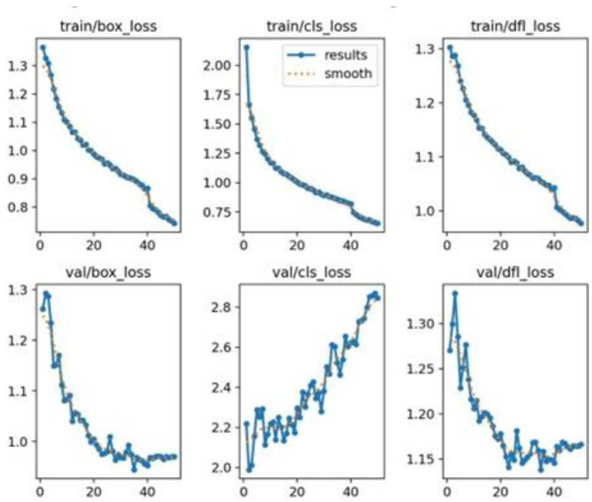

Figure. 3 Training and validation loss curves for bounding box and classification losses.

5.1.3. Detection Performance

Key performance metrics like Precision, Recall, F1 Score, and mAP were analyzed to evaluate YOLOv8n on the SCB dataset. These results indicate the model's ability to generalize across classes and scenarios.

5.1.4. Confusion Matrix

Absolute Values: The confusion matrix (Figure 4) shows accurate classification for the teacher, student, and background classes, with a high true positive count for the "student" class.

Journal of Information Systems Engineering and Management
2025, 10(33s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

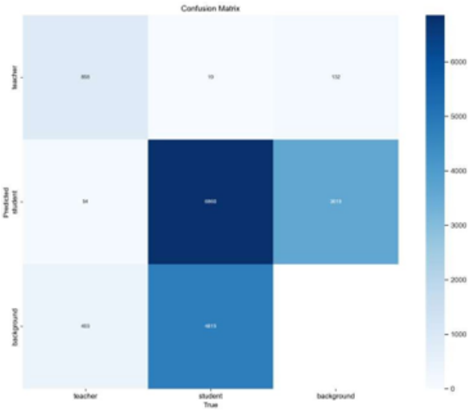

Figure. 4 Confusion matrix displaying absolute values for predictions on the SCB dataset.

5.1.5 Precision, Recall, and F1 Score Analysis:

Precision-Recall Curve: The precision-recall curve (Figure 5) highlights a mean Average Precision (mAP@0.5) of 0.541, with the "teacher" class achieving an mAP of 0.610 and the "student" class at 0.472. These values emphasize the robustness of YOLOv8n in detecting complex behaviors under real-world classroom scenarios.

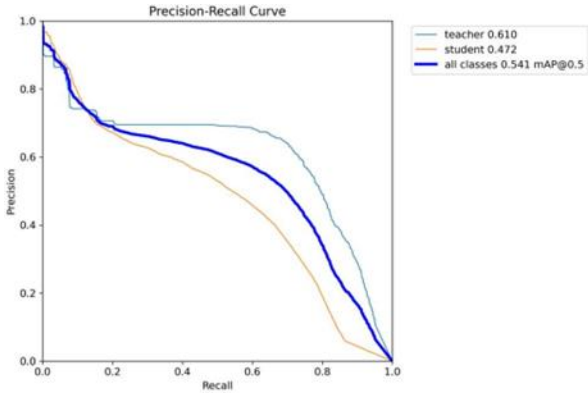

Figure. 5 Precision-recall curve for YOLOv8n across all classes.

5.1.6. Real-World Testing Performance:

To validate the practical applicability of YOLOv8n, the model was tested on real-world classroom footage where examinations were conducted. As shown in Figure 6, the model accurately identified students and teachers with consistent bounding box placement, even in densely populated and occluded scenarios.

Figure. 6 Detection results on a classroom scene

Journal of Information Systems Engineering and Management
2025, 10(33s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

5.2. YOLOv11n Results

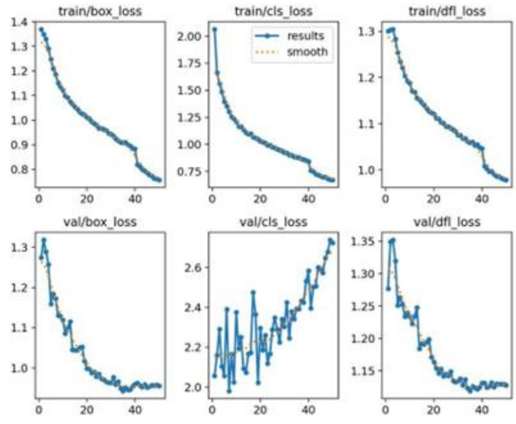

Figure. 7 Training and validation loss curves for YOLOv11n.

The YOLOv11n model was evaluated on the SCB dataset, achieving a mean Average Precision (mAP@0.5) of 0.582, with a precision of 0.78, recall of 0.64, and an F1 score of 0.63 at a confidence threshold of 0.286. The training and validation loss curves (Figure 7) demonstrated stable convergence over 50 epochs, with the validation loss stabilising earlier than YOLOv8n, indicating effective learning and generalisation during training on the SCB dataset.

Based on performance evaluation of a number of object detection algorithms, the optimal model to be used by the malpractice detection system was selected as YOLOv8. YOLOv8 is most suitable for applications that require the detection and classification of objects while having the lowest false positives and false negatives with high accuracy such as real-time monitoring in examinations. Although YOLOv11 was effective, it was less precise and suffered less recall in comparison to YOLOv8. So, the work of YOLOv11 stays as the next choice. As YOLOv11 had impressive results for object detection, its position still was after YOLOv8 in the case of distinction between relevant and irrelevant objects for malpractice detection. On the other hand, Fast RCNN and SSD performed poorly compared to YOLOv8 and YOLOv11. Fast RCNN, though it obtained a moderate F1 score, was not able to detect objects accurately, as its precision and recall values were lower. Although SSD was faster, it had major drawbacks in terms of recall, indicating that it could not detect objects in complex real-time scenarios. The precision-recall imbalance that was observed while using the SSD model revealed that it was failing to detect some relevant objects while also generating false positives. YOLOv8 emerged as the best performing model when taking into consideration the real time application of the model and its high accuracy and fast processing. It offered an ideal balance between speed, accuracy, and robustness across various conditions. With a capability of handling complex and dynamic environments, it was apt for this project, as it could be used as a stepping stone to detect malpractices accurately in examinations and thereby prevent it.

CONCLUSION AND FUTURE SCOPE

The performance measurement was done against YOLOv8 using other alternative models with similar objectives which includes SSD, Fast R-CNN and YOLOv11 and their F1 Scores, Precision and Recall metrics were compared. Since the environment being tracked is constantly changing, YOLOv8 is best suited and ideal for this environment with real-time object detection while also maintaining the smallest possible false negatives and positives possible. This software is based on the YOLOv8 model in terms of high speed, superior performance, and dynamic aptness for changing classroom settings. However, YOLOv8 does have a couple of its downsides: it has high computational needs, reliance on the quality of training data, and sometimes even false positives in complex environments. These requirements necessitate further optimization to be efficient and accurate in real-world applications. This model can be further combined with the techniques of pose estimation and action recognition to create a comprehensive malpractice detection system. The system proposed identifies suspicious behaviors like looking around, note passing, and unauthorized device use from live footage of classrooms. It will process live video feeds, identify objects such as mobile phones and notes, track the postures and movements of students, and classify their behaviors as normal and suspicious. The real-time decision- making module flags malpractice cases in their early stages.

The model's generalization might be enhanced by enlarging the dataset to encompass a variety of classroom settings, such as variations in lighting, seating configurations, and student conduct. Furthermore, YOLOv8's effectiveness and accessibility might be improved by optimizing it for devices with low resources using strategies like pruning and quantization. With these enhancements, the system would be more scalable, flexible, and efficient in maintaining academic integrity.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

ACKNOWLEDGEMENTS

We also would like to express our heartfelt gratitude to Dr. Divya James for her invaluable guidance, support, and encouragement throughout the course of this research. Her expertise and insightful feedback have played a significant role in shaping this work.

Finally, we extend our thanks to Rajagiri School of Engineering & Technology for providing an excellent academic environment, resources, and infrastructure to carry out this work.

REFERENCES

[1] Dang, M., Liu, G., Li, H., Xu, Q., Wang, X., & Pan, R. (2024). Multi-object behaviour recognition based on object detection cascaded image classification in classroom scenes. Applied Intelligence, 54(6), 4935–4951. https://doi.org/10.1007/s10489-024-05409-x

[2] Aziz, L., Haji Salam, M. S. B., Sheikh, U. U., & Ayub, S. (2020). Exploring deep learning based architecture, strategies, applications and current trends in generic object detection: A comprehensive review. IEEE Access, 8, 170461–170495. https://doi.org/10.1109/access.2020.3021508

[3] Liu, Q., Jiang, R., Xu, Q., Wang, D., Sang, Z., Jiang, X., & Wu, L. (2024). YOLOv8n_BT: Research on classroom learning behavior recognition algorithm based on improved YOLOv8n. IEEE Access. https://doi.org/10.1109/access.2024.3373536

[4] Xu, H., Zhang, J., Sun, H., Qi, M., & Kong, J. (2023). Analyzing students' attention by gaze tracking and object detection in classroom teaching. Data Technologies and Applications, 57(5), 643–667. https://doi.org/10.1108/dta-09-2021-0236

[5] Ren, Z., Zhang, H., & Li, Z. (2023). Improved YOLOv5 network for real-time object detection in vehicle-mounted camera capture scenarios. Sensors, 23(10), 4589–4589. https://doi.org/10.3390/s23104589

[6] Wang, A., Chen, H., Liu, L., Chen, K., Lin, Z., Han, J., & Ding, G. (2024). YOLOv10: Real-time end-to-end object detection. arXiv. https://doi.org/10.48550/arXiv.2405.14458

[7] Hussain, M. (2024). YOLOv5, YOLOv8 and YOLOv10: The go-to detectors for real-time vision. arXiv. https://doi.org/10.48550/arXiv.2407.02988

[8] Zhou, Q., Shi, H., Xiang, W., Kang, B., & Latecki, L. J. (2024). DPNet: Dual-path network for real-time object detection with lightweight attention. IEEE Transactions on Neural Networks and Learning Systems. https://doi.org/10.1109/tnnls.2024.3376563

[9] Wang, C., He, W., Nie, Y., Guo, J., Liu, C., Han, K., & Wang, Y. (2023). Gold YOLO: Efficient object detector via gather-and-distribute mechanism. arXiv. https://doi.org/10.48550/arxiv.2309.11331

[10] Shaikh, S. A., Chopade, J. J., & Sardey, M. P. (2023). Real-time multi-object detection using enhanced YOLOv5-7S on multi-GPU for high-resolution video. International Journal of Image and Graphics. https://doi.org/10.1142/s0219467824500190

[11] Tan, M., Pang, R., & Le, Q. V. (2020). EfficientDet: Scalable and efficient object detection. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). https://doi.org/10.1109/cvpr42600.2020.01079

[12] Terven, J., & Cordova-Esparza, D. (2023). A comprehensive review of YOLO: From YOLOv1 to YOLOv8 and beyond. arXiv. https://doi.org/10.48550/arxiv.2304.00501

Journal of Information Systems Engineering and Management
2025, 10(33s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

[13] Li, X., Wang, W., Wu, L., Chen, S., Hu, X., Li, J., Tang, J., & Yang, J. (2020). Generalized focal loss: Learning qualified and distributed bounding boxes for dense object detection. arXiv. https://doi.org/10.48550/arXiv.2006.04388
[14] Guo, A., Sun, K., & Zhang, Z. (2024). A lightweight YOLOv8 integrating FasterNet for real-time underwater object detection. Journal of Real-Time Image Processing, 21(2). https://doi.org/10.1007/s11554-024-01431-x
[15] Zhao, J., Zhu, H., & Niu, L. (2023). BiTNet: A lightweight object detection network for real-time classroom behavior recognition with transformer and bi-directional pyramid network. Journal of King Saud University - Computer and Information Sciences, 35(8), 101670–101670. https://doi.org/10.1016/j.jksuci.2023.101670
[16] Patel, S. (2024). Role of computer vision in retail stores. ResearchGate. https://doi.org/10.13140/RG.2.2.33928.94729
[17] Ghazi, D. S., Hamid, H. S., Zaiter, M. J., & Behadili, A. S. G. (2024). Snort versus Suricata in intrusion detection. Iraqi Journal of Information and Communication Technology, 7(2), 73–88. https://doi.org/10.31987/ijict.7.2.290
[18] Trappey, A. J. C., Lin, G. B., Chen, H. K., & Chen, M. C. (2023). A comprehensive analysis of global patent landscape for recent R&D in agricultural drone technologies. World Patent Information, 74, 102216. https://doi.org/10.1016/j.wpi.2023.102216
[19] Sun, Z., Xu, R., Zheng, X., Zhang, L., & Zhang, Y. (2024). A forest fire detection method based on improved YOLOv5. Signal, Image and Video Processing, 19(2). https://doi.org/10.1007/s11760-024-03680-6
[20] Saheed, Y. K., Abdulganiyu, O. H., & Ait Tchakoucht, T. (2023). A novel hybrid ensemble learning for anomaly detection in industrial sensor networks and SCADA systems for smart city infrastructures. Journal of King Saud University - Computer and Information Sciences, 35(5), 101532–101532.