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Implementation of YOLOv5 Algorithm for Exam Cheating Movement Detection

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ABSTRACT

The decline in academic integrity due to cheating during exams has become increasingly relevant, particularly following the shift to online learning systems. The absence of direct supervision in online exams creates opportunities for cheating practices that evade detection by the naked eye. This study addresses this challenge by developing an object detection model for cheating behavior using a deep learning approach based on the YOLOv5 algorithm. The dataset comprised 60 ten-second videos, extracted into 1,200 images representing four suspicious head movement patterns. Each image was manually annotated before training five YOLOv5 variants. Models were evaluated using object detection metrics (precision, recall, and mAP at IoU thresholds 0.5–0.95) and analyzed via confusion matrices. Results indicate that the YOLOv5x variant achieved peak performance, with mAP@0.5:0.95 of 83.06% and perfect classification accuracy across all classes. This demonstrates that an object detection–based approach provides a reliable preliminary solution for monitoring cheating during online exams.

KEYWORDS *YOLOv5, Cheating Detection, Computer Vision, Online Learning, Confusion Matrix*

INTRODUCTION

Education is the main foundation in producing superior human resources, both in terms of knowledge and moral integrity. The evaluation process in education, such as exams, aims to measure students' abilities objectively. However, honesty, which is the main foundation in the evaluation process, is often injured by fraudulent practices, such as cheating. This phenomenon is still a serious problem in the world of education and has the potential to weaken the quality of graduates as a whole.

Various studies have revealed that academic cheating occurs massively at various levels of education. A study on Parental Pressure, Perfectionism, and Academic Dishonesty in Students in Jakarta showed that about one-third of elementary school students had cheated on exams. A report from the Educational Testing Service (2010) notes that cheating practices at the high school level have increased sharply from 20% in 1940 to 75–98% today. At the college level, a Kessler International survey (2017) found that 86% of students have cheated at some point, while only 12% consciously cheated on ethical grounds (Lusiane & Garvin, 2019).

This problem is even more complex when the practice of cheating not only involves exam takers, but also receives support from educators. The Journal of Factors Affecting Cheating Behavior in Students and Students in Jakarta revealed the involvement of teachers, principals, and supervisors in helping students during national exams. The results of an online survey conducted by the Center for Applied Psychology of the Indonesian University of Education and published in October 2013 showed that cheating practices were carried out in an organized manner by the "success team" of the school itself (Cahyo & Solicha, 2017).

Along with the development of information technology, online and computer-based exams are increasingly being implemented. However, the implementation of this system presents new challenges in terms of supervision. The absence of the supervisor directly opens up opportunities for participants to commit various forms of fraud that are difficult to detect manually. Movements such as turning to the side, lowering your head, or looking at your phone often go unnoticed, especially when done subtly and repetitively.

Various studies have proposed artificial intelligence-based solutions to address this problem. Some approaches use CNN algorithms to detect head and eye movements during online exams with a high accuracy rate of up to 98.02% (Pangestu et al., 2024). Another study used the Feedforward Neural Network and successfully detected the potential for cheating with 100% accuracy and recall (Hadibrata & Rochadiani, 2024). On the other hand, the YOLOv5 algorithm is starting to show superior performance in visual detection, as in studies (Penggunaan et al., 2024a), (Bimantoro et al., 2024)and (Alkhalisy & Abid, 2023a), with an mAP of 89.2%, 55.5%, to 95%.

However, the detection performance in each study is still highly dependent on the YOLO variant used and the quality of the dataset involved. Research [6] shows that the YOLOv5s variant provides computationally lightweight results but relatively lower accuracy. While in the (Alkhalisy & Abid, 2023b), the combination of YOLOv5 with CBAM attention mechanism can increase accuracy by up to 95%. In addition, other approaches are also used, such as the Local Binary Pattern Histogram (LBP-H) (Wicaksono & Yamasari, 2025) dan FaceNet (Gopane et al., 2024), which focuses on face tracking and cheating gesture detection during online exams.

In addition, another study used the YOLOv4 algorithm which successfully detected various types of cheating such as turning their heads, lowering their heads, looking at their mobile phones, and cooperation between participants with an mAP of 86% (Nur et al., 2023). The 3DCNN-based model also showed effectiveness in detecting fraudulent gestures and prohibited objects with an accuracy of up to 95% (El Kohli et al., 2022). Meanwhile, research (Ramzan et al., 2024) showed that YOLOv5 was generally able to outperform the CNN model in detecting abnormal activity during online exams, although the specific precision values were not described in detail.

Looking at the trends and results of these studies, YOLOv5 is one of the promising algorithms for detecting cheating in online exams. This study aims to develop a visual detection model of suspicious behavior during the exam, using the YOLOv5 algorithm. The model is designed to recognize four main behaviors that are often associated with cheating: turning to the left, turning to the right, looking down, and looking at the phone.

Testing was conducted on several YOLOv5 variants to obtain the best model based on evaluation metrics such as precision, recall, and mAP. This research is focused on the development and evaluation stage of the model, as the initial foundation in the development of an automated proctoring system that supports the implementation of fair, transparent, and integrity online exams.

RESEARCH METHODS

The research method is a systematic plan or framework that contains a series of scientific steps that are carried out in a planned, controlled, empirical, thorough, and critical manner in an effort to understand a phenomenon or answer the formulation of a predetermined problem. This approach includes not only how data is collected and processed, but also how it is analyzed and interpreted to obtain scientifically valid and accountable findings. Through the right research methods, researchers can generate new knowledge, test hypotheses, or verify existing theories systematically and objectively. In this research method, the author refers to the skeletal model of Romi Satria Wahono (Romi Satria Wahono, 2012), which focuses its approach on four main components: Method, Parameters, Expected Results, and Outcome Evaluation.

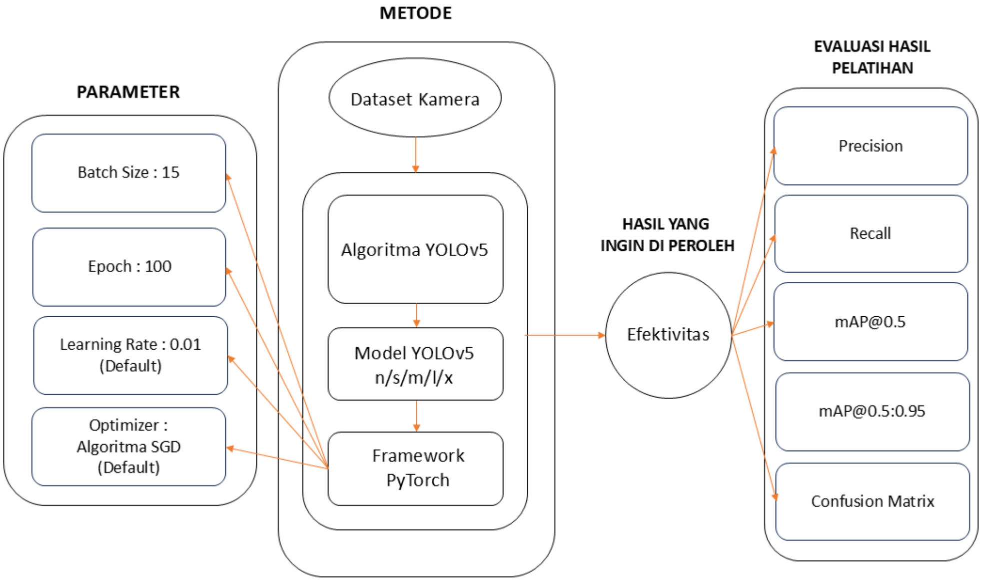

Figure 1. Research Methods

In this research method, a deep learning approach is used by applying the YOLO algorithm, which is one of the deep learning-based object detection algorithms known for its speed and accuracy in real-time processing(Penggunaan et al., 2024b). In this study, the YOLOv5 (You Only Look Once version 5) algorithm was used as the core of the process of detecting cheating behavior during the exam. The data used was a collection of camera images, which recorded the movements of the head and eyes of the test participants. The dataset is then processed and used to train various variants of the YOLOv5 model, namely YOLOv5n, YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x, using the PyTorch framework, which is one of the libraries in the Python programming language used to perform Deep Learning computing (Hendri et al., 2021). The training process is run in a Google Colaboratory environment. The system is designed to detect suspicious movement patterns such as turning to the left, turning to the right, lowering your head, and looking at the phone.

During the training process, a number of parameters are used to regulate the course of model learning. The model is trained with a batch size of 15, which means 15 data are processed at once in each iteration. The training lasted for 100 epochs, which is 100 complete repetitions of the entire dataset. The learning rate value used is 0.01, following the default settings in the YOLOv5 configuration. For the optimization process, the Stochastic Gradient Descent (SGD) algorithm is used, which is also the built-in optimizer of YOLOv5. All of these parameters are selected to ensure that the training process takes place stably and efficiently.

The main objective of this study was to measure how effective the model was in detecting cheating behavior during the exam. Effectiveness is measured by the model's ability to recognize suspicious objects or movements accurately and consistently, despite variations in image data. Thus, the model is expected to become a key component in a computer vision-based automated proctoring system that can be implemented in online exam situations.

To assess the model's performance after the training process, a number of evaluation metrics are used that are commonly applied in object detection tasks. The first metric is precision, which is used to measure the proportion of correct predictions to the total predictions made by the model. The second is recall, which shows how many objects or movements were successfully recognized from all the objects that should have been detected. The next evaluation uses the mean Average Precision (mAP) metric. A value of mAP@0.5 indicates the average precision of the model at the Intersection over Union

(IoU) threshold of at least 0.5, while mAP@0.5:0.95 reflects the average precision in a tighter IoU range, i.e. from 0.5 to 0.95. As a complement, a confusion matrix is also used to provide a visual representation of the distribution of correct and false predictions in each class, thus facilitating the analysis of the level of accuracy and patterns of misclassification that occur during the testing process.

RESULTS AND DISCUSSION

From the results of this study, the researcher conducted model training with 5 variants of the YOLOv5 Model including YOLOv5n, YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x. Using a dataset of 60 videos with a duration of 10 seconds with 15 participants and 4 movements that were extracted into the frame. Each participant from 1 movement was taken 20 frames resulting in a total of 1200 images that were labeled according to the four categories of cheating behavior in the exam. The training process lasted for 100 epochs with a batch size of 15, and was run on the Google Colaboratory Pro platform using the A100 GPU. Once the training process is complete, the performance of each model is evaluated using four key metrics: Precision, Recall, mAP@0.5, and mAP@0.5:0.95. These four metrics are derived from results.csv files that are automatically generated by YOLOv5 after the training ends. A summary of the evaluation results is presented in the following table.

Table 1 Model Training Results

Model	Precision	Recall	mAP@0.5	mAP@0.5:0.95
yolov5n	99.37	99.9	99.5	82.01
yolov5s	99.57	100.0	99.5	82.73
yolov5m	99.54	100.0	99.5	82.55
yolov5l	99.54	100.0	99.5	82.27
yolov5x	99.42	100.0	99.5	83.06

Based on the data in the table above, all models show excellent detection performance, characterized by high Precision and Recall values. This indicates that all five variants are able to recognize objects that represent exam cheating behavior with a very high degree of accuracy. All models recorded a mAP@0.5 value of 99.50%, which signifies consistent success in detecting objects at the IoU threshold of ≥ 0.5.

The difference in performance between models is more noticeable at the value of mAP@0.5:0.95, which reflects the accuracy of the model in various levels of detection accuracy. The YOLOv5x variant showed the highest performance with mAP@0.5:0.95 of 83.06%, followed by YOLOv5s (82.73%) and YOLOv5m (82.55%). This suggests that YOLOv5x has more stable and high-precision detection capabilities even at stricter IoU threshold variations.

Meanwhile, YOLOv5n as the lightest and smallest variant is still able to provide competitive results. With a Precision of 99.37% and a mAP@0.5:0.95 of 82.01%, this model can be an efficient alternative to systems with limited computing resources. The results of the Confusion Matrix will be described as follows.

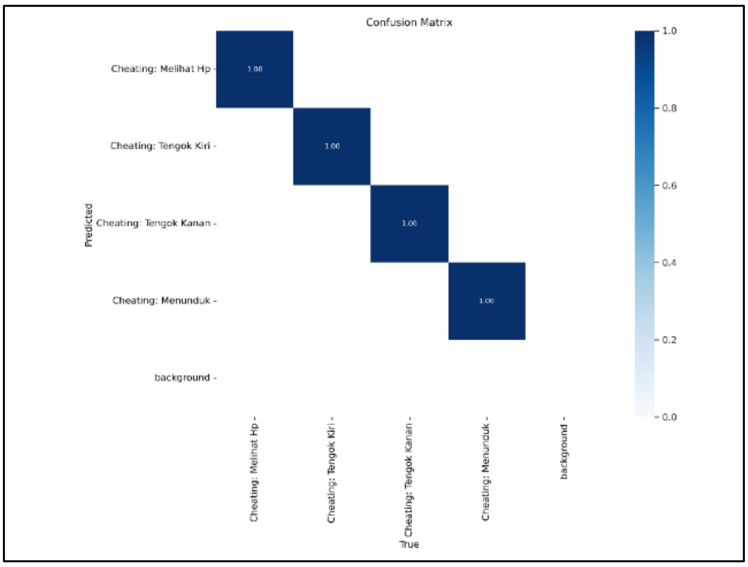

Figure 2. Confusion Matrix YOLOV5n

Based on the results of the confusion matrix, all predictions of the YOLOv5n model are exactly on the main diagonal with a value of 1.00 for each class. This shows that the model is able to classify all test samples with perfect accuracy, without generating misclassifications, either in the form of false positives or false negatives. This visualization is in line with previous quantitative metrics, where precision and recall values are close to 100%. Although YOLOv5n is the smallest variant in the YOLOv5 family, this achievement proves that the model is still able to accurately and reliably identify cheating behavior.

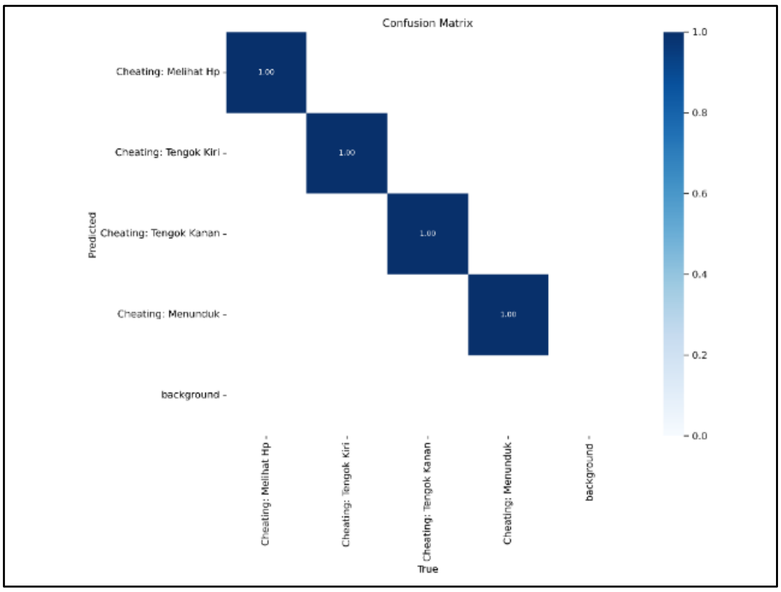

Figure 3. Confusion Matrix YOLOv5s

The confusion matrix of the YOLOv5s model shows very satisfactory performance. All predictions are located right on the main diagonal with a value of 1.00 for each class, i.e. looking at HP, turning to the left, turning to the right, and looking down. This indicates that the model is able to accurately classify each type of movement on the test data without any misclassification. This result is consistent with the value of the YOLOv5s model evaluation metric which recorded 100% accuracy and recall, and mAP@0.5 reached 99.50%. This confusion matrix visualization further strengthens that YOLOv5s not only excels in terms of size and speed efficiency, but is also able to provide high accuracy in detecting cheating behavior during exams

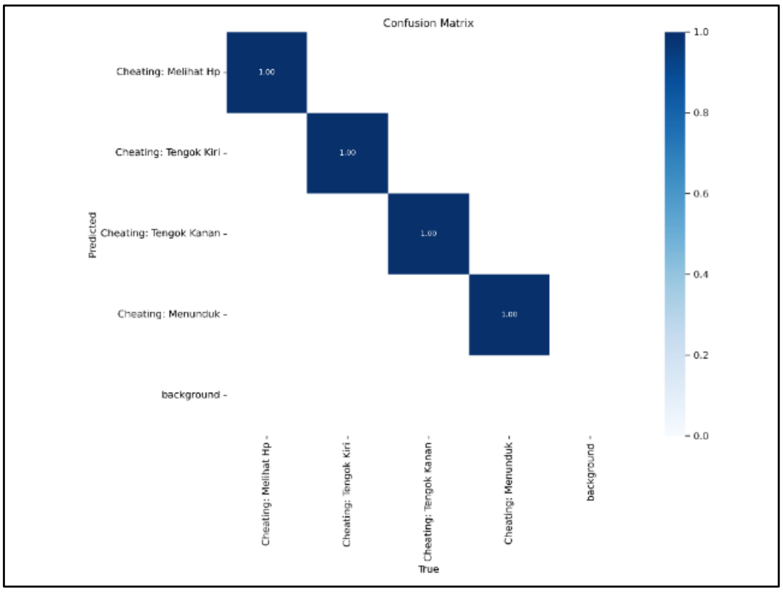

Figure 4. Confusion Matrix YOLOv5m

The confusion matrix in the YOLOv5m model shows a very high level of classification accuracy. As with the previous variant, all predictions are right on the main diagonal with a score of 1.00 for each class. This indicates that the model is able to perfectly recognize all four categories of target behavior in the test data. These results are consistent with the evaluation metrics achieved by YOLOv5m, namely perfect precision and recall, and a mAP@0.5 value of 99.50%. With this performance, the YOLOv5m is an ideal choice for the needs of systems that emphasize high accuracy, but still consider the relatively moderate model size.

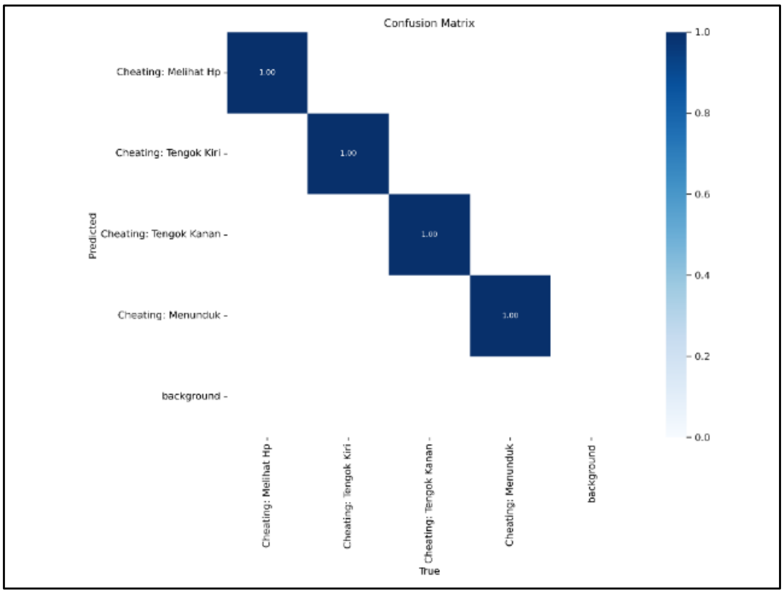

Figure 5. Confusion Matrix YOLOv5l

The visualization of the confusion matrix of the YOLOv5l model shows that this model has achieved perfect classification accuracy. The entire class looked at the HP, turned to the left, turned to the right, and lowered correctly classified, marked with a value of 1.00 on all the main diagonals with no errors between classes. This achievement is in line with other evaluation metrics, where the model recorded mAP@0.5 of 99.50% and mAP@0.5:0.95 of 82.27%, signaling consistent and high-precision detection capabilities in a variety of scenarios. This confusion matrix confirms that YOLOv5l is a solid choice, offering a balance between the complexity of a less heavy model and highly reliable performance

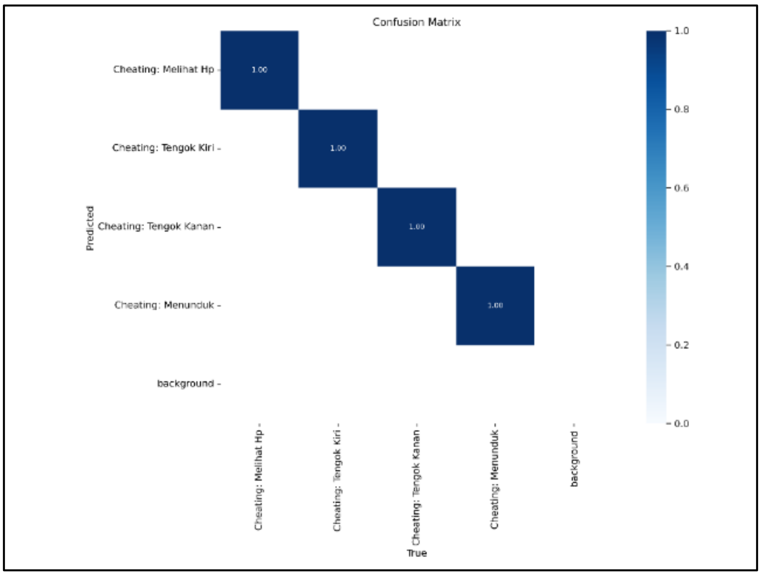

Figure 6. Confusion Matrix YOLOv5x

The YOLOv5x model, which is the variant with the largest size and the highest complexity in the YOLOv5 family, also shows excellent evaluation visual performance. Based on the confusion matrix, all predictions are located exactly on the main diagonal with a value of 1.00 in each class, which indicates the absence of misclassification in the test data. This model successfully identifies all categories of fraudulent behavior looking at the cellphone, turning to the left, turning to the right, and lowering with perfect accuracy. This achievement is in line with the highest mAP@0.5:0.95 score of 83.06% obtained by YOLOv5x, while strengthening its position as the best-performing model in this study.

Overall, all YOLOv5 variants tested in this study showed excellent ability to detect fraudulent behavior with a high level of accuracy. This is reflected in the near-perfect Precision and Recall values on each model, as well as a consistent mAP@0.5 at 99.50%. In addition, the visualization of the confusion matrix of the five models also strengthens the findings, where all predictions are exactly on the main diagonal. This means that each model is able to classify every type of behavior such as looking at the cellphone, turning to the left, turning to the right, and lowering their heads without any misclassification, both false positives and false negatives.

However, the difference in the value of mAP@0.5:0.95 is a crucial factor in evaluating the model's performance in more depth. These metrics provide a more comprehensive picture of the model's ability to accurately detect objects at various levels of Intersection over Union (IoU) thresholds. In this regard, YOLOv5x recorded the highest score, making it the most superior candidate for use on real implementation systems that require high accuracy and detection stability.

By considering all the results of the evaluation both quantitatively and visually, it can be concluded that each model has its own advantages. However, YOLOv5x emerged as the most optimal choice for the further stages of deployment because it was able to combine high accuracy, classification accuracy, and consistent performance under a wide range of data conditions.

After going through a comprehensive evaluation and analysis process, the YOLOv5x model was determined as the best model in this study. The next stage is to test the model's performance using new data that has never been used in training or validation before. The purpose of this test is to measure the extent of the model's ability to generalize to unknown data, as well as evaluate its performance in real-world scenarios, such as in the implementation of an online exam proctoring system.
An example of a visualization of the detection results can be seen in the following image:

Figure 7. Cheating: Seeing HP

In the image, for the detection of movement seeing the cellphone, an accuracy of 88% was obtained.

Figure 8. Cheating: left-looking movements

In the image, for the detection of left-looking movements, an accuracy of 67% was obtained.

Figure 9. Cheating: right-looking movements

In the image, for the detection of right-looking movements, an accuracy of 65% was obtained.

Picture. 10 Cheating: lowering movements

In the image, for the detection of lowering movements, an accuracy of 93% was obtained. The results of these tests show that the YOLOv5x model not only excels in training, but also has quite good generalization capabilities when tested with new data. Although there is a slight decrease in accuracy in the turning movement, the overall performance still shows that the model is feasible to be applied in a computer vision-based exam proctoring system.

CONCLUSION

This study demonstrates that the *YOLOv5x* variant effectively detects various forms of cheating behavior—such as turning left or right, lowering the head, and looking at a phone—during online exams, achieving a high *mAP@0.5:0.95* of 83.06% after training on 1,200 images over 100 epochs. The model also showed strong generalization when tested on new data, indicating its suitability for integration into automated proctoring systems to enhance academic integrity in online assessments. For future research, it is recommended to expand the dataset to include more diverse cheating behaviors and real-world scenarios, as well as to explore the integration of multi-modal data, such as audio or keystroke patterns, to further improve detection accuracy and robustness.

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