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Real Time Student Emotion Detection using Yolov5

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Abstract
The introduction of technology in the field of Education, especially in learner emotion detection plays an important role in the modern educational context. This research introduces the application of the YOLOV5 algorithm to detect learner emotions in real time during the classroom learning process. This research aims to see the performance of YOLOv5 in detecting student emotions by comparing YOLOv5 variants, namely YOLOv5m, YOLOv5n, YOLOv5l, YOLov5s, and YOLOv5x. The dataset used is a video recording of the learning process taken in classroom A3-02 in Building A, Informatics Engineering Study Program, Faculty, Engineering, University of Mataram, which is grouped into 3 classes, namely (Bored, Happy, and Neutral) with a total dataset of 451 images with dataset distribution divided into 87% training data, 8% validation data, and 4% testing data. Based on the tests conducted, YOLOv5m showed the best results with the highest accuracy reaching 89.60% on Mean Average Precision, with batch settings of 14 and epochs of 150. These results indicate that the YOLOv5 algorithm is effective in detecting learner emotions with a satisfactory level of performance and makes a significant contribution to learner emotion detection, underscoring the potential of this technology in enhancing interaction and learning in educational environments.

Keywords: emotion detection; education; computer vision; yolov5

INTRODUCTION

Technological developments in pattern recognition and machine learning in special expression recognition (FER) have been of great interest in recent decades (Zhong et al., 2023). Facial emotions in human interaction have an important role for a person to understand the intentions of others (Ko, 2018). There are two ways to express emotions, namely verbally and nonverbally (Lina et al., 2022). In the nonverbal category, facial expressions are one of the main ways to obtain information in interpersonal communication. Therefore, it is not surprising that there is a lot of research on facial emotions (Kaulard et al., 2012).

In human communication, facial expressions are helpful in understanding the intentions of others. In communicating between people, facial expressions are very helpful in understanding the intentions of others (Ko, 2018). Likewise in education, facial expression recognition plays an important role in classroom learning (Zhong et al., 2023). Emotional changes affect how individuals process information and learn. Students with unstable emotions will have difficulty in obtaining and capturing new information so that the learning process is less effective. Emotional stability plays an important role in the success of the learning process, as it impacts the learner's ability to concentrate and use their mind effectively (Wijanarko & Adhisa, 2023). The application of facial emotion recognition in the field of education can capture and record learner emotions, allowing teachers to know learner responses in real-time (Zhang et al., 2019). With a learner emotion recognition system, teachers can provide better guidance in developing a learning system that suits the learner's situation, making the learning process more interactive and effective (Widodo et al., 2022).

Object detection is a method in image processing and computer vision that is used in identifying an object in an image or video input dataset (Wijanarko & Adhisa, 2023). In recent years, the discovery of emotion detection has attracted significant attention in the computer science domain. Simultaneously, a number of researchers have tried to introduce *facial expression recognition* (FER) into the education and teaching domain (Zhong et al., 2023). Some of them are using the You Only Look Once method (Zhong et al., 2023), the Convolutional Neural Network method (Jaiswal & Nandi, 2020), the Haar-Cascade method (Riyantoko et al., 2021), and the VGG16 algorithm (Widodo et al., 2022).

Emotional state is very important in learning because it can affect how the learner receives, processes and stores information. The importance of the learner's emotional state in supporting the learning outcomes, hence the knowledge of the learner's emotional state is important for every teacher to have in order to be able to manage the learner's emotions so that they can adjust more varied learning methods to make the learning process effective. In the learning process, teachers may not be able to pay full attention to the emotional state of each learner, making it difficult for teachers to evaluate the emotional state of all learners at the same time, so a system is needed that can help teachers identify learner emotions in the learning process. YOLO (You Only Look Once) is an effective method for identifying learner emotions. Invented by Joseph Redmon for real-time object detection, YOLO stands out with its high accuracy (mAP) and higher frames per second (FPS) speed compared to similar systems. (Jaiswal & Nandi, 2020). The YOLO model framework supports Transfer Learning to recognize and classify novel objects. The released versions of YOLO include YOLOv1 to YOLOv8, which are known for their fast detection capabilities without compromising accuracy. YOLO enables real-time object detection with optimal performance, suitable for applications that require fast response such as autonomous vehicles, security surveillance, and facial recognition. YOLO has been proven to have relatively high speed and accuracy, and has been widely used in applications such as market research, security, and human-computer interfaces (Shaikh et al., 2023). With its advantages, the YOLO method is suitable for use in real-time facial emotion detection (Iskandar Mulyana & Rofik, 2022).

A comparative study between YOLOv5 and YOLOv7 has been conducted using different datasets, namely disease detection in rice plants (Bimantoro, 2024) and datasets for remote weapon detection (Olorunshola et al., 2023). The results show that YOLOv5 performs better when operating in resource-constrained environments. Another study in weapon detection showed that YOLOv5 provides higher accuracy than YOLOv7, with an accuracy difference of 4% (Bimantoro et al., 2024). So in this study, we used the YOLOv5 method, because previous research has not been used in detecting facial emotions in real-time during the learning process.

In previous research conducted by (Lina et al., 2022) utilizing Convolutional Neural Network (CNN) to recognize facial emotions in conference participants using video. However, these studies focused on the use of online conferencing and did not include applications for emotion detection in the context of classroom learning. Another study conducted by (Riyantoko et al., 2021) used the haar-cascade classifier method with the Fer2013 dataset to detect emotions. Meanwhile, this research uses the YOLOv5 method in detecting students' emotions during the process, because YOLOv5 has the ability to detect objects quickly and in real-time.

Many studies have used the YOLOv5 method in object detection, and this study also has similarities with previous studies. In previous research conducted by (Iskandar Mulyana & Rofik, 2022) the YOLOv5 method was used to perform real-time vehicle object detection. Research conducted by (Ashar & Suarna, 2022) on object detection of mask users using YOLOv5 was conducted in the governor's office environment. Whereas in research conducted by (Hasan & Lazem, 2023) emotion detection on human faces is done using the YOLO method with a dataset consisting of individual human face images, only detecting for one class.

However, in this research, emotion detection is performed using videos where one frame can contain several emotion classes at once.

The purpose of this study is to examine the performance of YOLOv5 in detecting learner emotions in real-time during the learning process. This research applies the YOLOv5 algorithm to identify learner emotions based on facial expressions which is expected to help teachers understand the dynamics of the ongoing class. This research is expected to provide a description of how the YOLOV5 algorithm works in detecting learner emotions in real-time and provide guidance to teachers in designing more interactive and effective learning techniques.

METHOD

This research is experimental research by testing the YOLOv5 algorithm which has several versions, namely YOLOv5m, YOLOv5n, YOLOv5l, YOLOv5s, and YOLOv5x to detect and classify objects in images. This method is implemented using Google Colab. The goal is to gain new insights from existing theories. The YOLOv5 algorithm receives an image as input, creates a bounding box, and outputs a prediction of the object class. The system flowchart is in Figure 1.

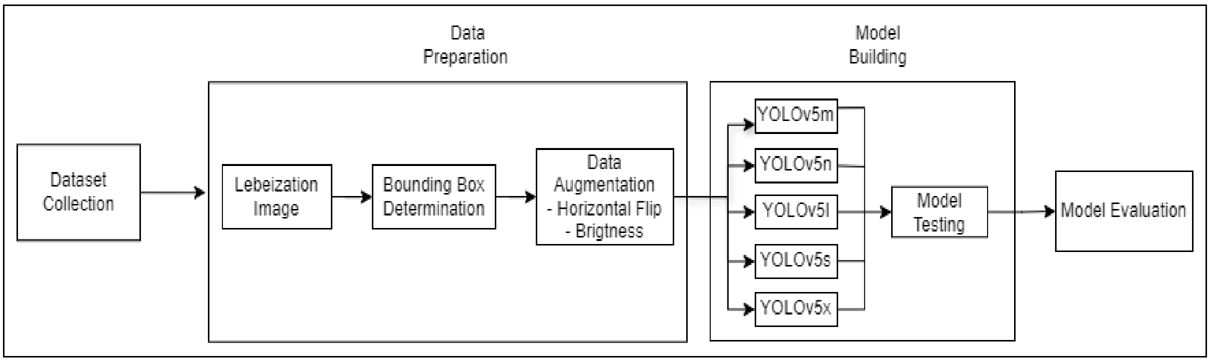

Figure 1. Flowchart of system development

In Figure 1, this is a system development flow consisting of four stages, starting with dataset retrieval, data preparation, model building and model evaluation. The first stage begins with taking a dataset which is carried out independently by researchers using a 1300D canon camera. Dataset collection was carried out in classroom A3-03 in Building A, Informatics Engineering Study Program, Faculty, Engineering, Mataram University. The next stage is data preparation where at this stage each image will be given lebelization, bonding box and data augmentation on the Roboflow platform. Roboflow is a platform available on the web that has many functions related to datasets (Maulana & Andika, 2023). Next is the model building stage by training data from each version of the YOLOv5 algorithm, namely YOLOv5m, YOLOv5n, YOLOv5l, YOLOv5s, and YOLOv5x. The best results from training data will be tested. Then the last stage will evaluate the performance of YOLOv5 in student emotion detection.

The YOLOv5 has several variants, such as the YOLOv5n, YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x. The main difference lies in the number of feature extraction modules and the number of kernels in the convolution layer in each version (Masurekar et al., 2022). The YOLOv5 architecture adopts some elements from the YOLOv4 model, and its model structure consists of Backbone, Neck, and Head (Dewi et al., 2022). YOLOv5 builds on the YOLO detection architecture by applying highly efficient algorithm optimization strategies, especially in the convolutional layer. The structure of YOLOv5 consists of four main components namely input, backbone, neck, and output (detect) (Fang et al., 2021). The network structure is shown in Figure 2.

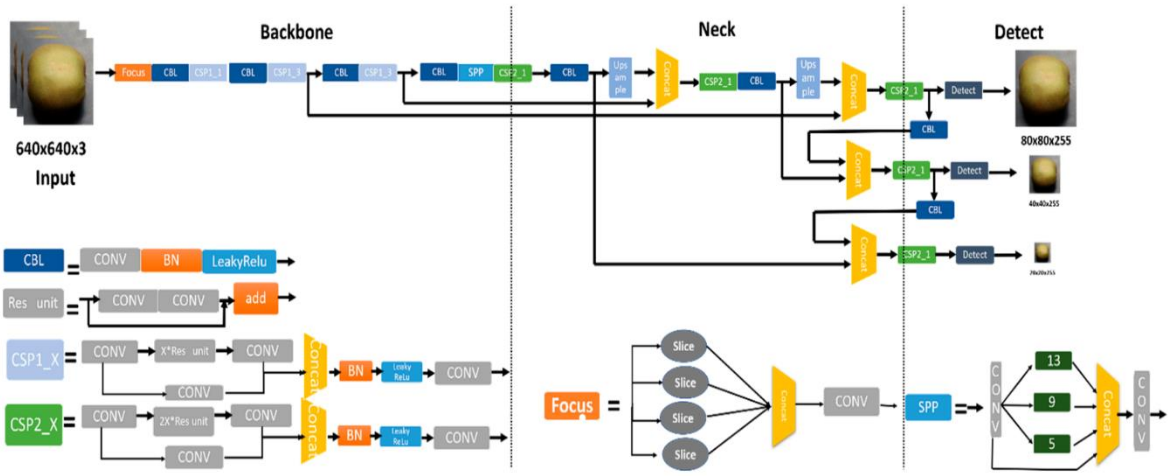

Figure 2. YOLOv5 architecture diagram (Jannah et al., 2022)

The input in YOLOv5 uses a mosaic data enhancement approach like YOLOv4, which has proven to be more efficient in detecting small objects. In addition, YOLOv5 also introduces an adaptive anchor frame calculation function. In the backbone part of YOLOv5, a structure called Focus is introduced which is used to perform slicing operations. In the neck of YOLOv5, there is the use of FPN-PAN structure, CSP2 structure adapted from CSPNet, and PANET as a component to combine features. This section mainly focuses on the formation of feature pyramids to improve the model's ability to detect objects with various scales. (Jannah et al., 2022).

RESULTS AND DISCUSSION

Results

Prior to training, a dataset of learner emotions from videos captured using a camera was prepared by converting the images into '.png' format. These images were then annotated and labeled using Roboflow for 3 classes: “Bored, Happy, and Neutral”. Object annotation was done by cropping the objects in the dataset and generating a metadata file in .txt format containing the coordinates (x, y, width, height) for each object.

In Figure 3, there is an image preprocessing process where data labeling is done with the number of classes, namely “Bored, Happy, and Neutral”, and bounding boxes on each student face in the image. The learner emotion dataset was augmented using Roboflow to prevent overfitting, including horizontal flip and brightness adjustment (-25% to +25%). After that, the dataset was divided into 20% for validation, 10% for testing, and 70% for training with an image size of 416x416. The distribution of the dataset after augmentation is 8% for validation data, 4% for testing data, and 87% for training data, which is set automatically by Roboflow after the augmentation process on the training dataset.

This research will test different versions of the YOLOv5 architecture with various parameters to get the best performance in emotion detection. Six training scenarios will be conducted for each version of YOLOv5, as shown in Table 1. In the experiment using YOLOv5m, the highest mAP value (89.6%) was achieved at epoch 150 with batch size 14, while the lowest value (75.5%) occurred at epoch 100 with batch size 8. This difference indicates that models with more epochs have more iterations to learn from the training data. Detailed experimental results can be seen in Table 2.

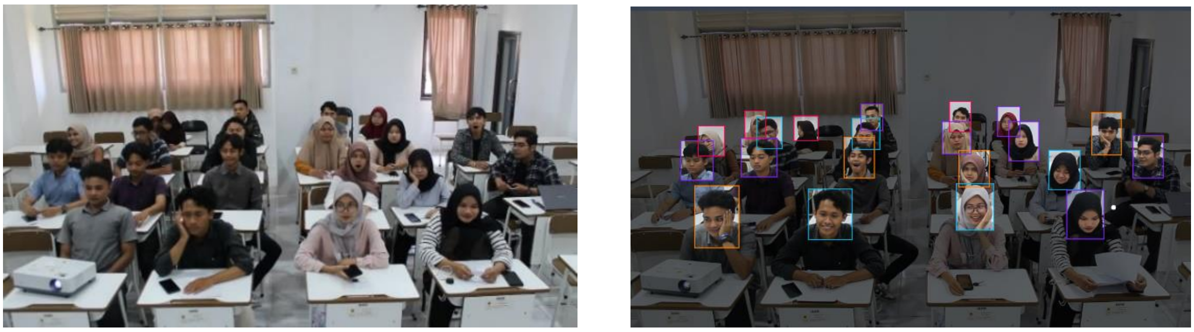

Figure 3. Data preparation

Table 1. Training scenario

Versi	*Batch*	*Epoch*
YOLOv5m	8	100 and 150
	14	100 and 150
	16	100 and 150
YOLOv5n	8	100 and 150
	14	100 and 150
	16	100 and 150
YOLOv5l	8	100 and 150
	14	100 and 150
	16	100 and 150
YOLOv5s	8	100 and 150
	14	100 and 150
	16	100 and 150
YOLOv5x	8	100 and 150
	14	100 and 150
	16	100 and 150

Table 2. YOLOv5m training results

Version	*Batch*	*Epoch*	*mAP*
YOLOv5m	8	100	75,50%
		150	89,20%
	14	100	88%
		150	89,60%
	16	100	89%
		150	88,30%

Table 3. YOLOv5n training results

Version	*Batch*	*Epoch*	*mAP*
YOLOv5n	8	100	86,60%
		150	87,80%
	14	100	86,10%
		150	87,50%
	16	100	87,80%
		150	87,90%

In the second experiment with YOLOv5n, the highest mAP value (87.9%) occurred at epoch 150 with batch size 16, while the lowest value (86.1%) occurred at epoch 100 with batch size 14. Of the 6 experiments using the YOLOv5n model, the mAP value obtained is still below the highest value using the YOLOv5m model. Detailed experimental results can be seen in Table 3. In the third experiment, with the YOLOv5l version, the highest mAP value was obtained at epoch 150 with a batch size of 16, which got an mAP value of 84.1%. While the lowest mAP value was obtained at epoch 100 with batch size 14, which amounted to 62.9%. Of the 6 experiments using the YOLOv5l model, the mAP value obtained is still below the highest mAP value using the YLOv5m model. The experiment results can be seen in Table 4.

Table 4. YOLOv5l Training Results

Version	*Batch*	*Epoch*	*mAP*
YOLOv5l	8	100	63,5%
		150	84,1%
	14	100	62,9%
		150	75,2%
	16	100	65,7%
		150	84,10%

In the fourth experiment using YOLOv5s, the highest mAP value (89.2%) occurred at epoch 150 with batch size 8, while the lowest value (87.2%) occurred at epoch 100 with batch size 8. From 6 experiments with YOLOv5s, the mAP value obtained is still below the highest value using the YOLOv5m model. Detailed experimental results can be seen in Table 5. In the fourth experiment using YOLOv5x, the highest mAP value (88.9%) occurred at epoch 150 with batch size 14, while the lowest value (87.7%) occurred at epoch 100 with batch size 8. Details of the experiment results can be seen in Table 6.

Table 5. YOLOv5s training results

Version	*Batch*	*Epoch*	*mAP*
YOLOv5s	8	100	87,2%
		150	89,2%
	14	100	87,9%
		150	88,7%
	16	100	87,9%
		150	89%

Table 6. YOLOv5x training results

Version	*Batch*	*Epoch*	*mAP*
YOLOv5l	8	100	87,7%
		150	86,9%
	14	100	87,9%
		150	88,9%
	16	100	88,3%
		150	88,6%

In Figure 4, the training and validation results using the YOLOv5m architecture viewed from the top left graph show a linear decrease in the box_loss value from 0.02 at the first epoch to 0.02 at the 150th epoch, indicating no overfitting. Objectness loss stabilizes from 0.07 to 0.03 in training, and from 0.055 to 0.035 in validation. A cls_loss value below 0.01 in training indicates an improved ability of the model in classification, while in validation it ranges from 0.025 to 0.005, indicating a good generalization ability of the learned pattern. Precision and mAP_0.5 reached 0.8, indicating good object detection capability. Although recall reached 0.8, mAP_0.5:0.95 was low, indicating difficulty in identifying object boundaries, especially in situations of overlapping or small objects.

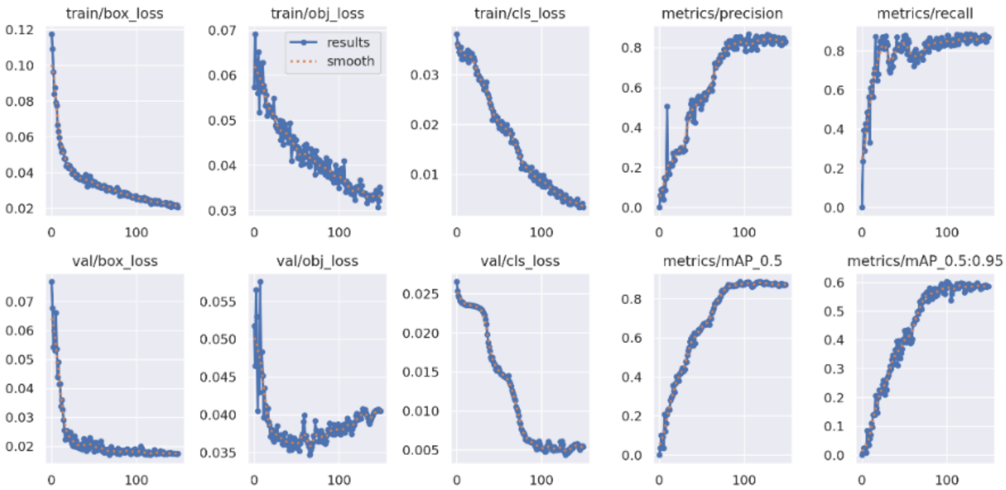

Figure 4. YOLOv5m training data graph

The implementation process is carried out on a dataset in the form of a video recorded in a classroom. The YOLOv5m model that has been generated from training and produces the best results is implemented on this dataset. The results of testing by using videos from the best model results, namely YOLOv5m to detect student emotions in the classroom during the learning process. The model testing results show that it can detect student emotions in three classes, with the Bored class marked with a red box with an accuracy of 0.83%, the Happy class marked with a pink box with an accuracy of 0.87%, and the Neutral class marked with orange with an accuracy of 0.85%. The testing results can be seen in Figure 5.

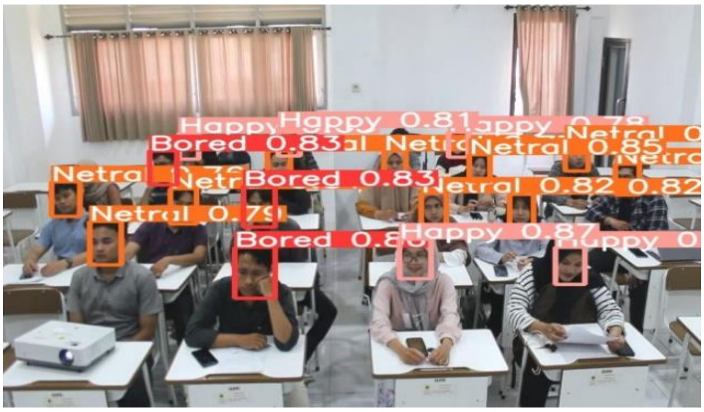

Figure 5. Testing result

Discussion

Tests were conducted with evaluated YOLOv5 architectures such as (v5m, v5n, v5l, v5s, and v5x) by comparing each version of Yolov5 with batch sizes of 8, 14, and 16 with epoch counts of 100 and 150. YOLO has a flexible architecture that can be adapted to the research being conducted. YOLOv5 has a version that can be customized according to user needs. In this study using the YOLOv5 architecture, the best performance was obtained in the YOLOv5m model with batch 14 and epoch 150 which had the highest mAP accuracy value of 89.60%. This is because YOLOv5m has sufficient size and architectural complexity to handle moderate object detection. The YOLOv5m model can maintain a balance between detection speed and accuracy, unlike the YOLOv5s which may not be powerful enough to handle long-range detection. Similarly, YOLOv5l and YOLOv5x may have large architectures for small datasets.

In car detection research YOLOv5m can also detect small target objects at a greater distance compared to other models (Du & Jiang, 2024). This is in line with research conducted on detecting student emotions where the target object is quite far away and small in size. However, based on their findings, there are still shortcomings because they have not been applied to the world of education and are still referring to non-academics. However, in this study YOLOv5 can be applied in the world of education and can detect student emotions during the learning process quite well. In this study, the scenarios offered to detect emotions work well as seen from the highest accuracy result of 89.60% using a video dataset, which allows detection of more than one emotion class in one frame. While in previous research using datasets in the form of individual face images can only detect one class of emotion getting an accuracy result of 94%. Therefore, the implementation of the YOLOv5 method in detecting emotions through video, with the ability to detect more than one class in one frame in real-time, produces performance almost comparable to previous research that only focuses on one class of emotion. From the tests that have been carried out YOLOv5m provides a better representation than smaller or larger versions. Using a batch size of 14 and an epoch of 150 is the optimal combination for the process of detecting learner emotions during the learning process by getting optimal results for the YOLOv5m model. So a sufficient number of batch sizes and epochs can allow the model to learn well without overfitting or underfitting. While the lowest accuracy value is obtained in the YOLOv5l model which has an mAP value of 62.9% with batch 14 epoch 100. This is because YOLOv5l has an architecture that is too complex for relatively small datasets, which can result in poor performance on smaller datasets. A smaller amount of training data can limit the ability of the model to learn complex patterns in the data, in this study the dataset used was still relatively small which resulted in the YOLOV5l model not having enough data to learn well in student emotion detection.

The implementation of YOLOv5m on a classroom video dataset demonstrates the model's ability to detect student emotions in real-time. However, there is potential to improve the performance of the model with further adjustments to the training parameters and dataset augmentation. This research makes an important contribution to the use of the YOLOv5 method for learner emotion detection, providing insight into the potential of this technology in supporting classroom interaction and teaching.

CONCLUSION

YOLOv5 was successfully implemented in real-time learner emotion detection during the classroom learning process. YOLOv5 provides a fairly good performance, seen from the results of the training test getting an mAP of 89.60%. The best mAP results are obtained in the YOLOv5m version which is able to produce emotion detection with optimal accuracy. The implementation of learner emotion detection using the YOLOv5 algorithm has great potential in improving classroom interaction and learning effectiveness. This can help teachers provide more adaptive responses to students' emotional states. In future research, it is hoped that the results of this research can be developed for an automatic detection system in detecting emotions in the learning process.

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