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A Robust Approach to Student Attendance Using Web-Based Facial Recognition

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Abstract
In this paper, we introduce an innovative student attendance recording system that utilizes computer vision and machine learning to improve attendance management in educational settings. By employing YOLOv8 for real-time face detection and MobileNetV2 for face recognition, the system achieves high accuracy and efficiency across various classroom conditions. Rigorous testing in diverse lighting environments and varying student densities demonstrated a peak recognition accuracy of 98% in well-lit conditions, with an average face detection time of under one second. This system offers a more robust, efficient, and scalable solution than traditional manual attendance methods, addressing common limitations in accuracy and reliability. Future work will target optimization under low-light conditions, enhancing its applicability in real-world scenarios.
Keywords: Automated Attendance, Computer Vision, YOLOv8, Face Recognition, Education Technology

INTRODUCTION
Student attendance is an essential aspect reflecting active participation and commitment in the learning process. A good attendance rate directly influences students' academic achievements and serves as an indicator for educational institutions to monitor student discipline and engagement in lectures. Therefore, accurate attendance data is crucial for educational institutions to uphold the quality standards of learning[1].

However, conventional attendance recording systems that rely on manual methods, such as filling out attendance sheets, often present various issues, including human error, data manipulation, and inefficiency in summarizing attendance data, especially in classes with a large number of participants [2]. This manual approach requires significant time and effort, making it less suitable for application in modern, technology-driven educational institutions. This situation creates a demand for more efficient solutions to manage student attendance processes.

Technological advancements, particularly in computer vision and machine learning, offer an alternative solution through automated attendance recording using camera-based facial recognition. This technology employs facial detection and recognition algorithms capable of operating in real-time to detect and record student attendance automatically, without the need for manual intervention. The YOLOv8 algorithm, as described [3], is known for its speed and efficiency in real-time object detection, making it highly suitable for dynamic classroom environments. Additionally, Convolutional Neural Networks (CNN) such as MobileNetV2 are chosen for their efficient architecture and ability to maintain high accuracy on devices with limited resources [4]. CNNs have demonstrated excellent performance in facial recognition, effectively classifying facial features [5].

Previous research conducted by Sun et al. (2023) demonstrated that the YOLOv5 algorithm with fusion features can detect faces under varying lighting conditions and handle challenges such as obscured or small faces in a classroom environment. However, this study will employ the more advanced YOLOv8 algorithm and integrate it with a CNN to improve accuracy and efficiency in automatically recording student attendance in the classroom. This system is expected to offer a more effective solution in addressing the challenges of facial detection in educational settings [6].

A similar study by Chowdhury et al. (2020) developed a classroom attendance recording system based on facial recognition using Convolutional Neural Networks (CNN), achieving up to 92% accuracy in identifying faces from video streams. While this study focused more on face detection and recognition for automatic attendance recording, the research conducted by the authors aims to develop a system with broader coverage for student attendance in classrooms. The YOLOv8 and CNN algorithms used are expected to provide higher efficiency and accuracy, particularly in larger and more dynamic academic environments, and to be integrated into a web-based application connected to the university's academic system [7].

Several previous studies have also explored the use of facial recognition technology for attendance systems, such as the work by Sun et al. (2023) using the YOLOv5 algorithm for face detection in classroom environments. Meanwhile, Chowdhury et al. (2020) developed a facial recognition system for class attendance with an accuracy of up to 92%. Although these studies successfully applied computer vision technology for attendance purposes, this research aims to develop a system with broader applicability, specifically for general student attendance in classrooms, leveraging the more advanced YOLOv8 and MobileNetV2 algorithms.

LITERATURE REVIEW

A web-based attendance management system has been designed as an effective solution for managing attendance in academic institutions. This system facilitates automated attendance recording based on predefined schedules, providing full support for educational institutions to efficiently manage student attendance records. It offers a three-tiered interface for administrators, staff, and students, enabling seamless interaction, efficient management, and effective analysis of attendance records. Users such as administrators can manage schedules, attendance parameters, and monitor attendance trends, while staff and students can record and access their attendance records. This system is designed to save time, reduce workload, and provide a modern solution for efficient attendance management in academic institutions [8].

Facial recognition has become one of the most prominent applications in computer vision and pattern recognition, with numerous applications across identification, access control, and human-computer interaction. This technology leverages the human face's unique characteristics as a biometric identifier, which is naturally accepted and non-intrusive. Facial recognition systems generally involve three main steps: face detection, feature extraction, and classification, often powered by deep learning algorithms such as Convolutional Neural Networks (CNNs). These systems achieve high accuracy in controlled environments, although performance may degrade in unconstrained conditions with variations in lighting, pose, and facial expression [9].

YOLOv8 has emerged as one of the most advanced object detection algorithms, offering significant improvements in accuracy and speed compared to its predecessors. It incorporates several architectural innovations, including a CSPNet backbone and an FPN+PAN neck, which enhance feature extraction and multi-scale object detection. YOLOv8 also adopts an anchor-free approach, simplifying training and boosting detection accuracy. These enhancements make YOLOv8 highly efficient for real-time applications, positioning it as a suitable choice for dynamic environments like classrooms due to its capability to maintain high accuracy and efficiency under various conditions [10].

In facial recognition research, Convolutional Neural Networks (CNNs) are extensively used for their proficiency in extracting essential visual features from image data. CNNs operate by learning a hierarchy of features, beginning with simple edges and progressing to more complex patterns, allowing them to classify and recognize various objects within images. This hierarchical feature extraction is facilitated by the architecture of CNNs, which comprises convolutional layers for capturing spatial hierarchies, pooling layers for dimensionality reduction, and fully connected layers for classification tasks. These layers work in tandem, enabling CNNs to achieve high accuracy in complex visual tasks such as facial recognition [11][12].

Transfer learning is a widely used approach in the development of CNN models, as it enables faster model training and enhances accuracy by utilizing pre-trained models from related tasks. This technique leverages knowledge from prior tasks, allowing models to apply previously learned features to new but similar tasks, thus improving performance in situations where training data may be limited. Transfer learning strategies, such as inductive and transductive learning, are especially beneficial in domains with scarce target data, as they facilitate efficient learning through connections between source and target domains [13].

For devices with limited resources, MobileNetV2 has proven to be an efficient architecture. MobileNetV2, with its inverted residuals and linear bottleneck design, reduces memory usage and computational costs while maintaining high accuracy. This efficient structure makes MobileNetV2 particularly suitable for mobile and embedded applications, as it minimizes both computational overhead and resource demands, ensuring optimal performance on low-power devices [14].

OpenCV and Python have become essential tools in the field of computer vision and image processing. OpenCV is an open-source library widely used for image processing tasks, providing a range of functions that support operations such as image reading, color conversion, and contour detection. Combined with Python, which offers a robust and flexible programming environment, OpenCV allows developers to implement efficient and scalable solutions for various image analysis tasks, including structural similarity analysis and thresholding techniques [15].

MATERIALS & METHODS

The research steps are presented in Figure 1 below.

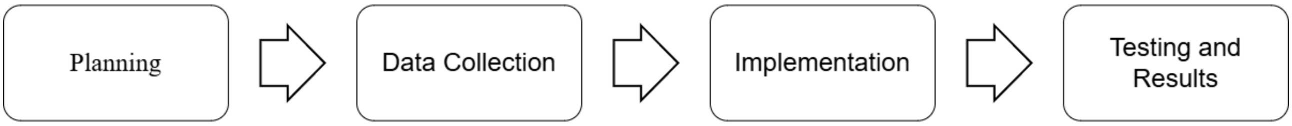

Figure 1. Research Steps

The data collection process involved capturing student facial images using a camera from a single viewpoint. Each image underwent preprocessing, including conversion to grayscale, normalization, and resizing to 160x160 pixels. Data augmentation was also applied to increase variation in the training data, including horizontal flipping, rotation, zooming, and brightness adjustment.

The collected data were then labeled with student ID numbers and names and split into two parts: 80% for training data and 20% for testing data. This augmentation aimed to improve the model's performance in recognizing faces under various lighting conditions.

The system implementation was carried out by integrating two algorithms: YOLOv8 for face detection and CNN MobileNetV2 for facial recognition. The YOLOv8 algorithm is used to detect and count faces from video streaming in real-time. Once a face is detected, CNN MobileNetV2 is employed to recognize and classify it.

Each facial recognition result is matched with data stored in the student database. If the face is recognized, attendance data, such as name, student ID, and recognition accuracy, is saved in a MySQL database. This system operates automatically and in real-time through a web interface developed using the Flask framework.

Testing was conducted to evaluate the system's performance in detecting and recognizing student faces. The tests were performed under two conditions.

1. Lighting Conditions: The system was tested under different lighting conditions, including bright and dim environments.
2. Real-Time Testing: The system was tested in a classroom with varying numbers of students, ranging from 10 to 40.

Performance measurement was conducted using a Confusion Matrix to calculate metrics such as True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN). Additionally, testing was carried out to measure the system's speed in detecting and recognizing faces. The average time to recognize a face after detection was less than 1 second.

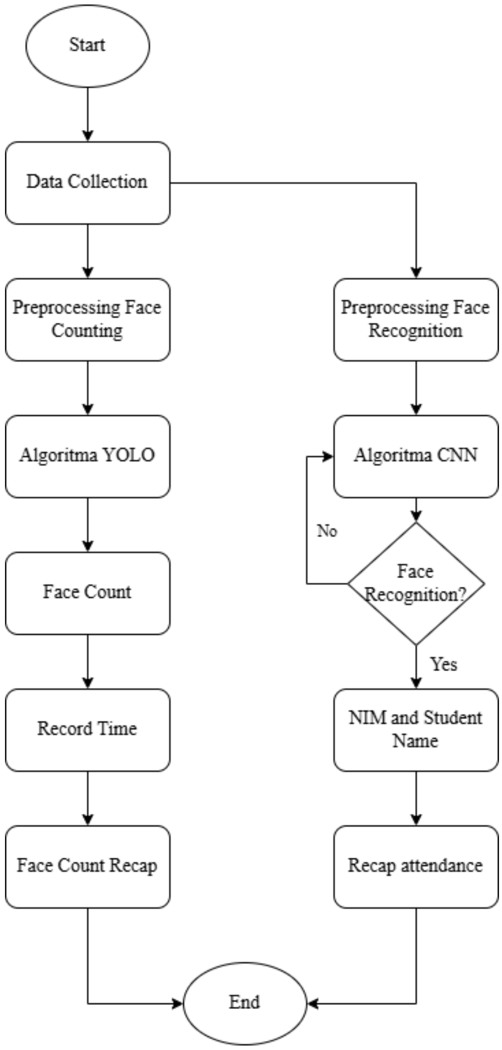

Figure 2. Flowchart System

The process begins with facial data collection from a connected camera. This data is then processed in two stages. First, preprocessing is conducted to count the number of detected faces, and second, preprocessing is performed for facial recognition. The system uses the YOLO (You Only Look Once) algorithm to detect faces in the video, producing a count of detected faces. Next, a Convolutional Neural Network (CNN) algorithm is employed to recognize the detected faces. Once a face is identified, the system checks if it is recognized. If the face is not recognized, no further data is recorded. However, if the face is recognized, the system records the student's ID and name. This data is then summarized to produce an attendance record for that time.

RESULTS AND DISCUSSION

The facial recognition model training was conducted using the MobileNetV2 architecture with data augmentation to enhance model performance and accuracy. Training was carried out over 50 epochs with an 80:20 split between training and validation data.

During the training process, several callbacks were applied, such as Early Stopping to halt training when there was no improvement in validation accuracy after several epochs, and Model Checkpoint to save the best model during training.

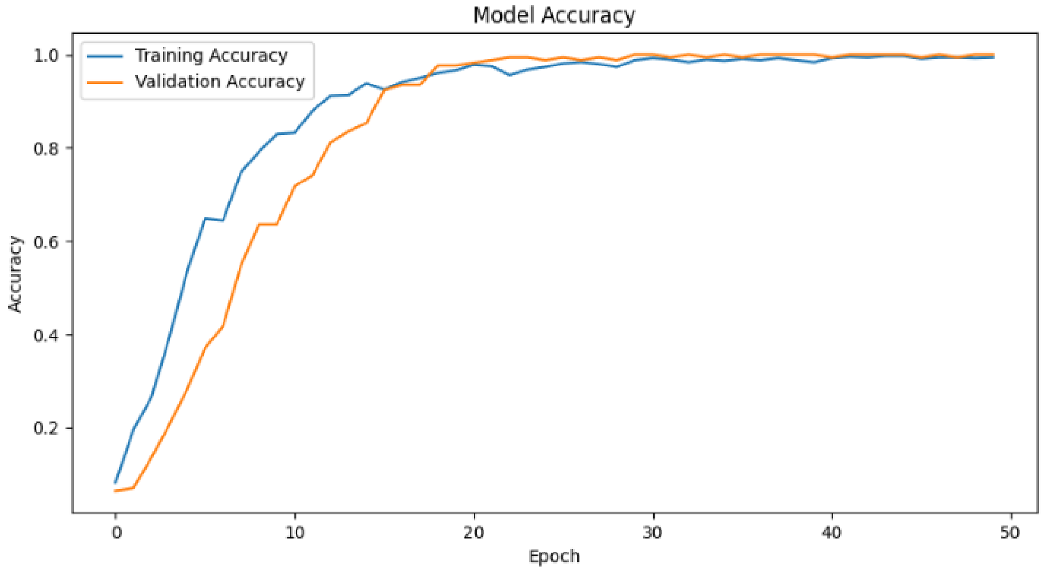

Figure 3. Model Accuracy

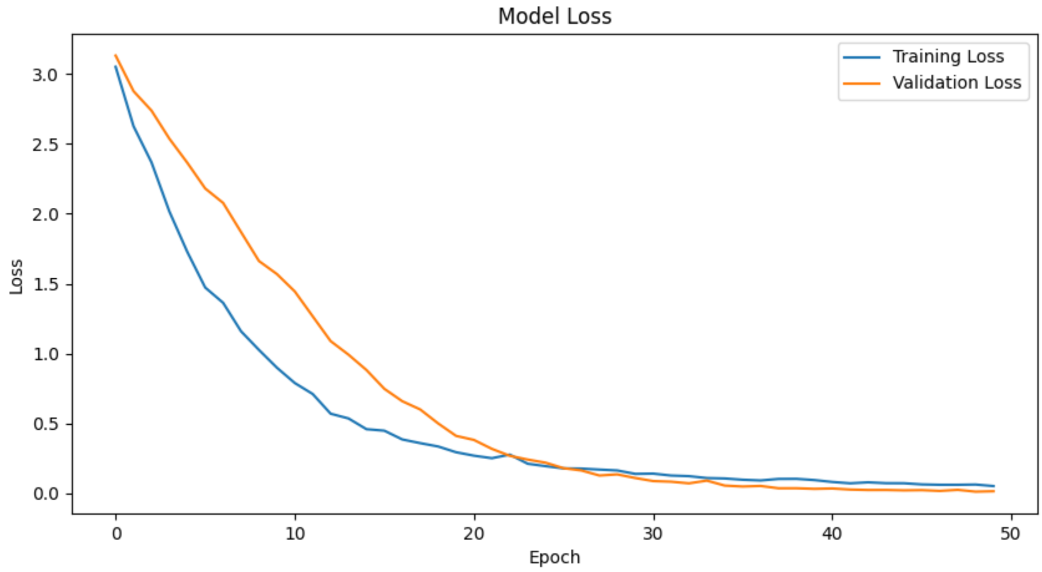

Figure 4. Model Loss

Figure 3 shows the accuracy changes during training, while Figure 4 illustrates the loss changes throughout the training process. Based on the graphs, it can be observed that the model achieves stable validation accuracy after several epochs, with a minimal difference between training and validation accuracy, indicating that the model does not exhibit significant overfitting.

The facial recognition model achieved a validation accuracy of 99% on the validation data. This accuracy indicates that the model can recognize student faces with a high level of confidence, particularly after the data augmentation process was applied to enhance the variety of facial images used.

Table 1. Model Performance Evaluation

Metric	Value
Training Accuracy	99%
Validation Accuracy	99%
Validation Loss	0.03

Table 1 above presents the final evaluation results of the model. The relatively low loss value on the validation data indicates that the model is not only accurate but also performs well in correctly classifying student faces.

After the facial recognition model was trained, the system was tested in real-world conditions using a camera to detect and recognize student faces in real-time. Testing was conducted in a classroom of 17 students under standard room lighting with a single camera viewpoint.

The system utilizes YOLOv8 for face detection and MobileNetV2 for recognizing the detected faces. Each recognized face is then recorded in the MySQL database, including the name, student ID, and recognition accuracy. The following are the test results across various scenarios.

1. Under optimal lighting, the system was able to detect and recognize faces with high accuracy, achieving an average recognition accuracy of 97%. The system could also recognize faces in less than 1 second after YOLOv8 detected them.
2. In dim lighting, facial recognition accuracy dropped to around 60%, with some faces not well detected by YOLOv8. However, successful facial recognition still maintained an adequate level of accuracy.
3. When the camera was positioned further away from a direct line of sight, face detection accuracy remained high. However, facial recognition accuracy decreased to 75% as some facial features were not clearly visible.

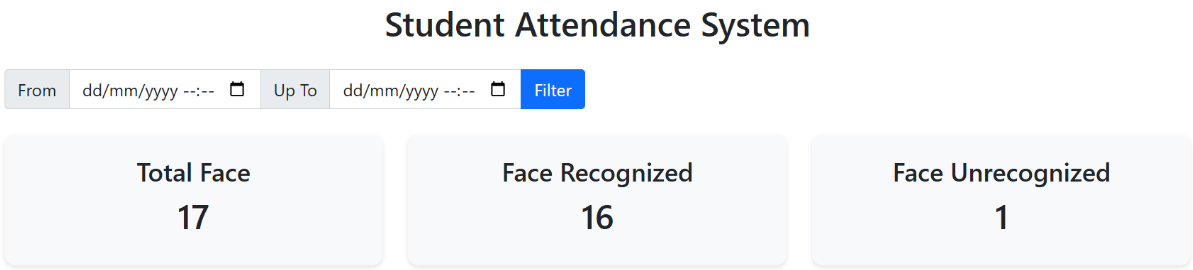

Figure 5. Student Attendance System Interface with Detected Face Data

Figure 5 shows the results from testing in a class of 17 students. The results indicate that the system successfully recognized 16 faces with a fairly high accuracy. One face was not recognized because the student was looking down when entering the classroom.

Based on the tests conducted, the following analysis of system performance can be made.

1. The system is able to detect faces in real-time and recognize them in under 1 second, making it suitable for use in classrooms with a large number of students. The use of YOLOv8 is highly effective for quick face detection, even with a significant number of students in the classroom.
2. The MobileNetV2 model provides good accuracy in facial recognition. However, under low lighting conditions, when faces are obstructed, or when the camera is too far, accuracy tends to decrease. This indicates that the quality of captured images greatly impacts facial recognition results.
3. Data augmentation used during model training (such as flipping, rotation, and brightness adjustment) helps the model become more resilient to changes in lighting conditions and face angles. However, there is still room for improvement in handling extremely low-light conditions.

The facial recognition system testing results showed varying accuracy levels for each student. The figure below presents data for 16 students along with their student IDs and facial recognition accuracy in percentages. The obtained accuracy levels demonstrate the model's effectiveness in recognizing student faces in a classroom environment, with an average recognition accuracy of 97%.

Show 25 entries Search:

Name	NIM	Accurasy	Time
Atrida	210170028	97.00%	2024-10-29 14:08:21
Yolinda	210170208	98.00%	2024-10-29 14:08:19
Wirda	210170033	96.00%	2024-10-29 14:08:17
Syifa	210170280	98.00%	2024-10-29 14:08:16
Salma	210170193	95.00%	2024-10-29 14:08:15
Riska	210170267	96.00%	2024-10-29 14:08:13
Putri	210170281	98.00%	2024-10-29 14:08:09
Lidaini	210170223	98.00%	2024-10-29 14:08:07
Lala	210170123	97.00%	2024-10-29 14:08:04
Eriska	210170169	98.00%	2024-10-29 14:08:03
Dila	210170032	97.00%	2024-10-29 14:08:02
Citra	210170063	98.00%	2024-10-29 14:08:00
Caca	210170054	97.00%	2024-10-29 14:07:59
Azmi	210170261	98.00%	2024-10-29 14:07:41
Ari	210170114	98.00%	2024-10-29 14:07:40
Dika	210170126	96.00%	2024-10-29 14:07:39

Showing 1 to 16 of 16 entries Previous 1 Next

Figure 6. Student Attendance List

As shown in the figure, the system was able to recognize student faces with a fairly high accuracy, with some students achieving up to 98% accuracy. This high accuracy indicates that the system is reliable in an optimal classroom environment, although there may be some variation influenced by factors such as face position, lighting, and distance.

CONCLUSIONS

This study successfully developed a student attendance recording system based on facial recognition using computer vision and machine learning technology, employing the YOLOv8 algorithm for face detection and MobileNetV2 for facial recognition. The system is capable of automatically recording attendance with an accuracy of up to 98% under optimal lighting conditions, and demonstrates fast performance in face detection and recognition. This system is expected to enhance the efficiency and accuracy of attendance management in educational institutions, although further optimization is needed to improve performance under low-light conditions.

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