STUDENT ATTENDANCE BASED ON FACE RECOGNITION USING THE CONVOLUTIONAL NEURAL NETWORK METHOD

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Abstract—*Mataram University of Technology (UTM) still relies on a manual attendance process, such as signing paper-based attendance lists, which are prone to fraud and difficult to manage on a large scale. This study develops a face recognition-based attendance system using Convolutional Neural Network (CNN), which can automatically recognize visual patterns and unique facial features. CNN has advantages in extracting significant facial features, allowing it to recognize faces under various lighting conditions and viewing angles. The dataset used consists of 5,820 facial images from 97 students, with 60 augmented images per student. The results indicate that this system can be implemented in a lecture environment, achieving a validation accuracy of 98.5% at the 150th epoch. However, the model has some limitations, such as a relatively small dataset size and challenges in recognizing faces under extreme lighting conditions or unusual angles, which can affect accuracy in real-world applications. Additionally, although this system has the potential for real-time implementation, further optimization is required to ensure fast and accurate responses on a large scale. To overcome these limitations, future research can explore the use of direct camera input to enhance efficiency and user experience. Furthermore, improving dataset quality by incorporating variations in lighting and image angles, as well as exploring alternative deep learning architectures such as Vision Transformers (ViT) or Swin Transformer, can enhance model performance and generalization. By implementing these improvements, the facial recognition-based attendance system can be more optimal in enhancing accuracy and ease of use in academic environments.*

Keywords: *attendance, CNN, face recognition, students.*

Abstrak—*Universitas Teknologi Mataram (UTM) masih mengandalkan proses absensi manual, seperti menandatangani daftar hadir berbasis kertas, yang rentan terhadap kecurangan dan sulit dikelola dalam skala besar. Penelitian ini mengembangkan sistem absensi berbasis pengenalan wajah menggunakan Convolutional Neural Network (CNN), yang mampu mengenali pola visual dan fitur wajah unik secara otomatis. CNN memiliki keunggulan dalam mengekstraksi fitur wajah signifikan, sehingga dapat mengenali wajah dalam berbagai kondisi pencahayaan dan sudut pandang. Dataset yang digunakan terdiri dari 5.820 gambar wajah dari 97 mahasiswa, dengan 60 gambar hasil augmentasi per mahasiswa. Hasil penelitian menunjukkan bahwa sistem ini dapat diterapkan dalam lingkungan perkuliahan, dengan akurasi validasi mencapai 98,5% pada epoch ke-150. Namun, model ini memiliki beberapa keterbatasan, seperti ukuran dataset yang masih relatif kecil serta tantangan dalam mengenali wajah di bawah kondisi pencahayaan ekstrem atau sudut yang tidak biasa, yang dapat mempengaruhi akurasi dalam aplikasi dunia nyata. Selain itu, meskipun sistem ini memiliki potensi untuk diimplementasikan secara real-time, masih diperlukan optimalisasi agar dapat memberikan respons yang cepat dan akurat dalam skala besar. Untuk mengatasi keterbatasan ini, penelitian selanjutnya dapat mengeksplorasi penggunaan input kamera secara langsung guna meningkatkan efisiensi dan pengalaman pengguna. Selain itu, peningkatan kualitas dataset dengan menambahkan variasi pencahayaan dan sudut pengambilan gambar, serta eksplorasi arsitektur deep learning alternatif seperti Vision Transformers (ViT) atau Swin Transformer, dapat meningkatkan kinerja dan generalisasi model. Dengan menerapkan perbaikan ini, sistem absensi berbasis pengenalan wajah dapat lebih optimal dalam meningkatkan akurasi dan kemudahan penggunaan di lingkungan akademik.*

Kata Kunci: *presensi, CNN, pengenalan wajah, mahasiswa.*

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INTRODUCTION

Mataram Technology University (UTM) is a private university located in Mataram City, West Nusa Tenggara Province. The university is home to more than 1,000 active students who participate in academic community activities. One of the primary academic activities at UTM, conducted routinely from Monday to Saturday, is the lecture process, following the class and lecture schedules that have been established.

Currently, UTM employs a manual approach for documenting lecture activities. A key component of this process is recording student attendance during lectures, which is performed by lecturers and students alike. Student attendance serves as a crucial indicator for evaluating academic participation and the overall effectiveness of the lecture process. However, like many other educational institutions, UTM still relies on traditional attendance systems, such as manual signatures or identity cards. These methods are prone to fraud, time-consuming, and challenging to manage at scale. Consequently, there is a pressing need for an innovative solution to enhance the efficiency and accuracy of the attendance system.

In response to this need, Mataram Technology University aims to develop a facial recognition-based attendance system. Facial recognition technology offers a promising alternative to overcome the limitations of traditional methods (Joshi et al., 2023)(Qi et al., 2023). By utilizing the unique and immutable features of an individual's face, this technology provides a secure and reliable approach to attendance recording without requiring additional devices such as cards or fingerprint scanners (Abdulameer et al., 2023). Within the context of lectures, facial recognition offers a more practical and dependable method for recording student attendance (Andini et al., 2022).

The development of this application will utilize the Convolutional Neural Network (CNN) method. CNN is a deep learning algorithm that has demonstrated exceptional performance in visual pattern recognition tasks, including facial recognition (Qi et al., 2023). It automatically extracts critical features from facial images, ensuring robustness against variations such as lighting, camera angles, and facial expressions (Qi et al., 2023; Widi Wiguna et al., 2023).

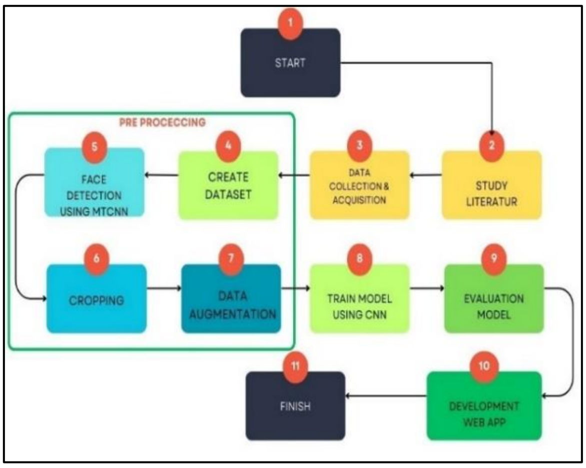
Some comparisons of the accuracy of the CNN method with other methods are as follows: the Convolutional Neural Network (CNN) method demonstrates superior performance in face recognition, achieving 100% accuracy on training data and 98% on test data (He & Ding, 2023). Other methods, such as Support Vector Machine (SVM), have lower accuracy, specifically 61.39% when applied to facial expression classification (Agus Aryawan I Putu, 2023). Meanwhile, the k-Nearest Neighbors (KNN) algorithm exhibits high accuracy, reaching 99.20% in face classification (Silitonga & Damanik, 2021). Additionally, the combination of the ISOMAP method with KNN has been tested, achieving 88.33% accuracy in face recognition (Kosasih, 2020).

Several related studies demonstrate various approaches to facial recognition systems. For instance, (Sintawati et al., 2023) designed a smart locker using LBPH, while (Rahmad, ST., M.Kom., Dr. Eng. et al., 2022) developed a CNN-based student attendance application with an accuracy of 77.27%. (Andini et al., 2022) created a GUI-based attendance system achieving 85% accuracy, and (Sugeng & Mulyana, 2022) employed dlib and KNN methods for LAN web-based attendance, attaining 98.3% accuracy. Similarly, (Alwendi & Masriadi, 2021) utilized the Fisherface method with a detection rate of 65%, and (Susim & Darujati, 2021) applied PCA eigenface for facial recognition. (Satwikayana et al., 2021) developed a web-based automatic attendance system for Zoom meetings using CNN, achieving 92% accuracy.

This study aims to design and develop a facial recognition-based attendance application tailored to the specific needs of Mataram Technology University. The research is expected to deliver an innovative and practical solution that enhances the efficiency and accuracy of the attendance system. Additionally, it seeks to demonstrate the reliability of CNN in addressing real-world facial recognition challenges within the context of UTM's academic environment.

MATERIALS AND METHODS

The research process consists of several stages, as illustrated in Figure 1.



Source: (Research Stage, 2024)
Figure 1. Research Stage

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In this study, several stages will be undertaken to develop a facial recognition-based student attendance application using the CNN method. The process begins with a study literature, followed by data collection and acquisition, data preprocessing, model training using CNN, model evaluation, and the deployment of the attendance application. Below is an explanation of the stages according to the diagram in Figure 1.

Studi Literature

This stage involves reviewing previous studies relevant to facial recognition using Convolutional Neural Networks (CNN) to understand the fundamental concepts, identify optimal approaches and optimization methods, and find research gaps for further development (Salehi et al., 2023). The literature review serves as the foundation for selecting the methods used in this study, such as the MTCNN algorithm for face detection and CNN for model training (Shafiq & Gu, 2022).

Data Collection and Acquisition

Data is a crucial component in developing deep learning-based systems. In this stage, student facial datasets were collected through the following methods:

1. Direct Photo Capture – Student photos were taken at Universitas Teknologi Mataram from three different angles left, right, and front capturing each angle only once while ensuring that images were taken from the upper body to prevent the system from being influenced by clothing patterns.
2. Handling Occlusion Conditions – Students wearing masks were asked to remove them before the photo was taken to ensure that all facial features were clearly detected, whereas students wearing glasses were allowed to keep them on so the model could recognize faces with and without glasses.
3. Lighting Condition Variations – Photos were taken under various lighting conditions, including indoor environments with fluorescent lighting, dim lighting, and natural light from windows, to enhance the model's robustness against different lighting conditions during attendance recognition.

After collecting the data, the images were categorized based on student identities to facilitate labeling, which is essential for supervised learning tasks (Drukker et al., 2023; Li, 2021).

Preprocessing

This stage aims to ensure that the data is prepared for training the CNN model. The process involves several sub-stages:

1. Create dataset

The collected dataset was structured into an appropriate format for model training, such as storing face images in separate folders based on student identities (Öztürk & Erçelebi, 2021).

2. Face detection using MTCNN

Multi-Task Cascaded Convolutional Neural Networks (MTCNN) are employed to detect faces in each image. MTCNN is a highly accurate algorithm capable of detecting faces even under poor lighting conditions or when face orientations are misaligned (Guo et al., 2022)(Gu et al., 2022). This study initially used Haar Cascade for face detection, but the results were suboptimal as it mistakenly identified patterns on batik clothing as facial features, leading to detection errors. This issue occurred because the images were taken from the upper body. To address this, MTCNN was selected for its superior accuracy in face detection, ensuring that the model correctly identifies facial regions.

3. Cropping

After detecting the face, the image is cropped to retain only the facial area. This step removes background noise and other irrelevant elements, improving the focus of the dataset (Kavitha et al., 2022).

4. Data Augmentation

To enhance data diversity, augmentation techniques such as rotation, flipping, lighting adjustments, and scaling are applied. These augmentations make the model more robust to variations in the data (Mumuni & Mumuni, 2022; Saragih & To, 2022).

Train Model Using CNN

The CNN model is designed and trained using the processed dataset. This process includes the following steps (Satwikayana et al., 2021):

1. CNN Architecture: The selection or design of the CNN architecture, such as using FaceNet, ResNet, or a custom model.
2. Model Training: The dataset is used for training with optimization algorithms such as Adam or SGD, employing loss functions like cross-entropy for face recognition.
3. Validation: The dataset is split into training and validation sets to prevent overfitting and ensure the model generalizes well to unseen data.

Evaluation Model

The trained model is evaluated to assess its performance (Aldiani et al., 2024). This stage includes evaluating the model using metrics such as accuracy, precision, recall, F1-score, and the confusion matrix. Additionally, real-world testing is performed by applying the model to unseen data (test data) to ensure its ability to generalize to new, real-world scenarios.

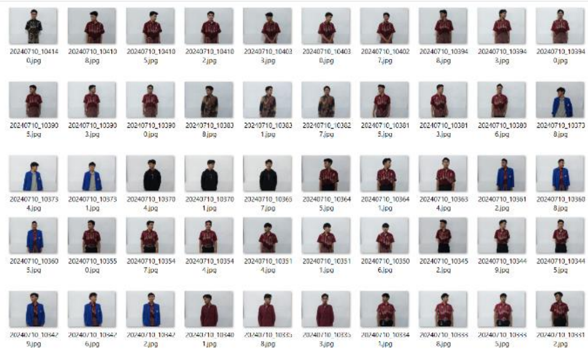
Development Web App

Once the model is ready, the final step is to integrate it into a web-based application for the attendance system (Dzhangarov et al., 2021; Verma et al., 2021). This stage involves selecting a web framework, such as Flask or Django, to build the application. The CNN model is then integrated into the backend of the application to detect and recognize faces in real time. Additionally, the application is equipped with a user interface to facilitate the management of attendance data and facial recognition results. To ensure smooth real-time processing, the system was tested on a Lenovo laptop with an AMD Ryzen 3 5300U processor (2.60 GHz) and 8GB of RAM. The facial recognition model processes each image within **0.5 to 1 second**, depending on factors such as image resolution, background complexity, and lighting conditions. Optimizations were implemented, including efficient preprocessing techniques and GPU acceleration where available, to minimize latency and enhance performance. These improvements ensure that student identities can be verified quickly and attendance recorded without noticeable delay.

RESULTS AND DISCUSSION

Data Collection and Acquisition

At this stage, the process of collecting student data was carried out across three different classes in the Informatics Engineering study program at Mataram Technology University, with a total of 97 students. The data collected consisted of student images taken from the front, left, and right sides. In this study, training on raw images before preprocessing was not conducted because the initial dataset consisted of half-body images that contained background and non-facial elements. During the data collection stage, student images were captured from the front, left, and right angles, covering the upper body. Since the facial recognition-based attendance system only requires the facial area as the main focus, using raw images without preprocessing could reduce the model's accuracy due to the presence of non-facial elements that may interfere with facial feature learning. Without preprocessing, the model might mistakenly learn patterns from clothing or background elements as primary features, leading to suboptimal facial recognition performance. Therefore, preprocessing techniques such as face detection using MTCNN, cropping, and data augmentation were applied to ensure that the dataset contained only facial features. This step is crucial for improving the model's focus on facial characteristics and ensuring an effective training process, ultimately enhancing the accuracy of face recognition in the developed attendance system. The collected data is shown in Figure 2 below.



Source: (Research Results, 2024)
Figure 2. Student Photos from the Front, Left, and Right Sides

Preprocessing

Before the model training process using the CNN method begins, data pre-processing is performed to improve the quality of the data. Several pre-processing steps are carried out at this stage, including:

1. Create Dataset

After the dataset is collected, as shown in Figure 2 above, the next step is to organize the dataset by placing each student's image into a folder named after the Student Identification Number (NIM). This will serve as the label for each student, as illustrated in Figure 3.

Source: (Research Results, 2024)
Figure 3. Student Dataset

2. Face Detection Using MTCNN

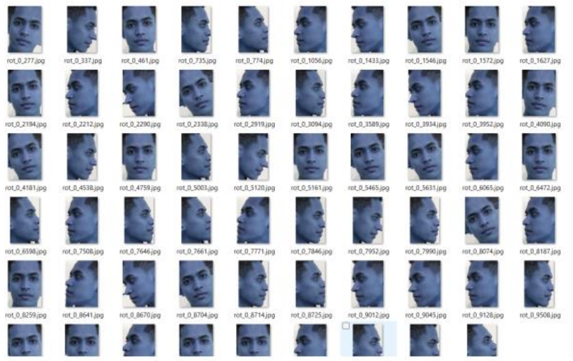
This study focuses on student face recognition as the primary basis for a face recognition-based attendance system. Therefore, face detection is performed to ensure that only the student's facial area is analyzed, which improves recognition accuracy and minimizes the risk of errors caused by detecting areas other than the face. This step also ensures that the data used in the face recognition stage is more specific and relevant, thereby supporting the reliability of the attendance system being developed. At this stage, the MTCNN method is used, as it is capable of detecting faces accurately and efficiently. The face detection process is illustrated in Figure 4.

Source: (Research Results, 2024)
Figure 4. Face Detection Using MTCNN

3. Cropping
Since this study focuses on student faces, cropping is performed to retain only the facial area, ensuring that the resulting features are of higher quality. After the face detection process, the next step is to crop the image to preserve only the student's face. This helps eliminate irrelevant features, improve the efficiency of the model training process, ensure data consistency, and enhance data accuracy. Therefore, this stage is crucial in developing a face-based attendance system. The cropping process is shown in Figure 5.

Source: (Research Results, 2024)
Figure 5. Croping Images

4. Data Augmentation
The CNN method is highly effective in processing image data; however, its performance heavily depends on dataset variation. At this stage, a standard data augmentation process is applied to increase variation and enhance accuracy. Augmentation involves randomly rotating images up to 20 degrees clockwise or counterclockwise to simulate facial position variations in real-world scenarios. Each student's facial image is augmented 20 times, resulting in a total of 60 images per individual, expanding the dataset to 5,820 images from 97 students. This augmented dataset provides a comprehensive representation of possible facial student, forming the foundation for improving model accuracy. Further analysis of the augmentation's impact on accuracy is presented in Table and Figure 6, while the results of the augmentation process are illustrated in Figure 6.



Source: (Research Results, 2024)
Figure 6. Data Augmentation

Train Model Using CNN

After the data augmentation is completed, the next step is training the model using the CNN method. The training process is conducted three times with different epoch values: 50, 100, and 150, using a batch size of 32. The model consists of three convolutional layers, three max-pooling layers, ReLU and Softmax activation functions (Softmax is used for multi-label classification), a dropout rate of 50%, and is optimized using the Ada optimizer. However, because the dataset consists of only 97 students and augmentation was performed to increase the number of images, there is a risk that the model may overfit to the artificially generated variations rather than learning meaningful facial features. Overfitting occurs when the model memorizes the training data instead of generalizing from it, making it less effective when exposed to new, unseen images. While data augmentation helps improve model diversity, it does not fully replace the need for genuine variations in facial expressions, lighting conditions, and poses. This limitation can lead to biased predictions, where the model performs well on the augmented training set but struggles with real-world data that contain natural variations not present in the training set. Additionally, since the images were taken from only three specific angles (left, right, and front), the model may struggle to recognize faces under more challenging conditions, such as different lighting environments, occlusions (e.g., partially covered faces due to masks or hands), and more dynamic head positions (e.g., tilted or rotated perspectives). In real-world scenarios, students may not always face the camera directly, and their faces may be subject to various distortions, including motion blur or changes in facial expression. These factors can significantly impact the accuracy of the model when applied outside controlled environments. To mitigate these challenges, future improvements should consider increasing the dataset's diversity by collecting images from multiple perspectives, capturing real-world variations such as different

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lighting setups, and integrating additional data augmentation techniques such as Gaussian noise, random occlusions, and contrast adjustments. Additionally, incorporating pre-trained models through transfer learning could enhance generalization, leveraging knowledge learned from large-scale face recognition datasets. The CNN model and the training results are shown in Figure 7 and Table 1 below.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 126, 126, 32)      896

 max_pooling2d (MaxPooling2D  (None, 63, 63, 32)       0
 )

 conv2d_1 (Conv2D)           (None, 61, 61, 64)        18496

 max_pooling2d_1 (MaxPooling  (None, 30, 30, 64)       0
 2D)

 conv2d_2 (Conv2D)           (None, 28, 28, 128)       73856

 max_pooling2d_2 (MaxPooling  (None, 14, 14, 128)      0
 2D)

 flatten (Flatten)           (None, 25088)             0

 dense (Dense)               (None, 128)               3211392

 dropout (Dropout)           (None, 128)               0

 dense_1 (Dense)             (None, 97)                12513

=================================================================
Total params: 3,317,153
Trainable params: 3,317,153
Non-trainable params: 0
_________________________________________________________________
```

Source: (Research Results, 2024)
Figure 7. CNN Model Architecture

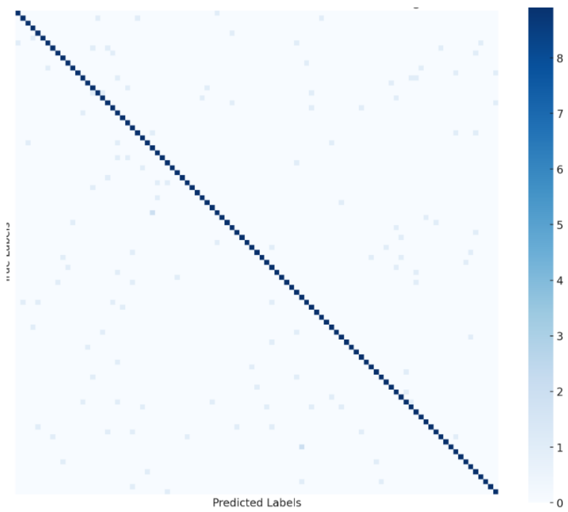
Table 1. Model Training Results

Epoch	los	Acc	Val_Los	Val_Acc
50	1.24	60.7%	0.52	85.3%
100	0.52	82.5%	0.10	97.4%
150	0.45	85.6%	0.06	98.5%

Source: (Research Results, 2024)

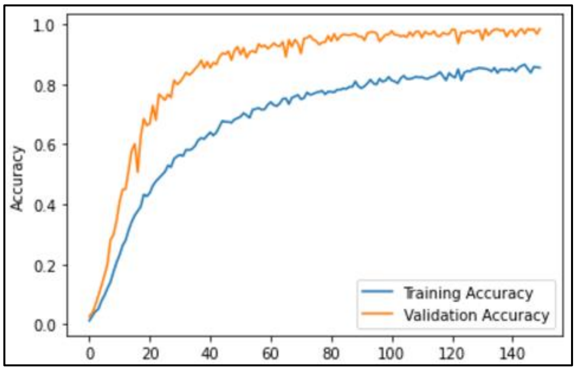
As shown in Table 1 above, increasing the number of epochs during training significantly improves both training and validation accuracy while drastically reducing the error rate. This trend indicates that the model, through repeated exposure to the training data, gradually refines its parameters and learns to capture essential features required for accurate classification. Simply put, with each epoch, the model becomes better at recognizing and generalizing patterns in the dataset. However, increasing the number of epochs does not always yield positive results. Beyond a certain point, the model may experience overfitting, where it becomes too closely adapted to the training data and loses its ability to recognize new patterns effectively. This risk is particularly high when working with datasets that have limited variations, such as in this study, which includes only 97 students with a limited number of images despite data augmentation. In such cases, the model tends to memorize specific details in the training data, including noise or patterns that do not truly reflect general facial characteristics, thereby reducing accuracy when encountering new, more diverse images. To address this issue, the early stopping technique can be applied to automatically halt training when validation performance no longer improves, preventing overfitting and ensuring better generalization.

To further evaluate the model's performance, the confusion matrix is presented in Figure 8, providing a detailed breakdown of prediction accuracy for each class. This matrix helps assess how well the model differentiates individuals, identifies classification errors, and highlights areas for improvement. Based on the generated confusion matrix, the model demonstrates high accuracy, with most predictions aligning with the diagonal elements, indicating correct classifications. However, some misclassifications still occur, particularly among individuals with similar facial features or under different lighting conditions. Certain classes exhibit higher misclassification rates than others, suggesting that the model still struggles to distinguish individuals with similar facial characteristics. To mitigate this issue, increasing the amount of training data with broader variations—such as through more aggressive augmentation techniques or the addition of new datasets can be beneficial.



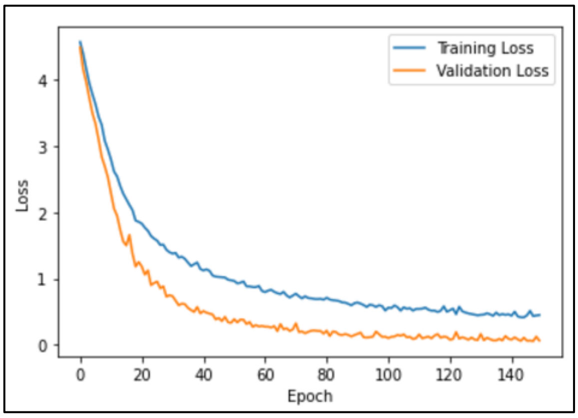
Source: (Research Results, 2024)
Figure 8. Confusion Matrix for Model Performance Evaluation

Additionally, computational efficiency is a crucial factor in real-time attendance applications. The average computation time per epoch during model training was recorded at approximately 59.22 seconds, depending on the system specifications used (Lenovo AMD Ryzen 3 5300U with Radeon Graphics, 8GB RAM). This processing speed is a critical aspect to ensure that the model can be implemented in real-time without constraints. The process of accuracy improvement and error reduction is also illustrated in Figures 9 and 10.



Source: (Research Results, 2024)

Figure 9. Accuracy Improvement



Source: (Research Results, 2024)

Figure 10. Error Rate Decrease

While the results show that accuracy improves as the number of epochs increases, a few important factors must be considered. First, the possibility of overfitting should be carefully checked, especially since the dataset was largely augmented rather than gathered from real-world situations. Second, the limited variety in the dataset may affect how well the model performs under different conditions. Future work should aim to expand the dataset to include a wider range of facial expressions, lighting conditions, and angles to improve the model's ability to generalize. Additionally, trying other augmentation techniques or different deep learning architectures may help lower the risk of overfitting and make the model more robust.

Development Web App

Once the model creation process is complete, the next step is to develop a web-based application using the Flask framework and Bootstrap 5. This application takes a student's face image as input, processes it, and performs attendance by recognizing the face. Since this system is intended for real-time use, processing latency is a crucial factor. Although large-scale testing has not yet been conducted, potential challenges can be anticipated. The recognition time per student depends on factors such as model complexity, hardware performance, and system load. As the number of students increases, the system may experience higher latency due to the computational overhead. To optimize real-time performance, future work may involve testing the application with a larger dataset and implementing enhancements such as model quantization, GPU acceleration, or asynchronous processing. The web-based application is shown in Figure 11.

Source: (Research Results, 2024)

Figure 11. Face-Based Attendance Application

CONCLUSION

Based on the research conducted using internal student data from Mataram University of Technology, the development of a face-based attendance application using the CNN method has been successfully implemented. The best training accuracy was achieved at epoch 150, with a training accuracy (Acc) of 85.6% and a testing accuracy (val_acc) of 98.5%. Currently, the facial recognition attendance process is carried out by uploading facial images to the developed web application. Based on this trial, student attendance can be determined. However, for further research, several improvements can be made to enhance the model and overall attendance process. One potential improvement is using live camera input instead of manually uploaded images to improve real-time performance. Expanding the dataset to include more students can also help improve model generalization. Additionally, enhancing dataset quality by increasing variation in lighting, angles, and image resolution can further refine the system's robustness. Another possible enhancement is exploring alternative deep learning architectures, such as Vision Transformers (ViT) or Swin Transformer, to compare their performance with CNNs. By implementing these enhancements, the system can be optimized for better accuracy and efficiency in real-world applications.

The distinction of this research lies in the development of a facial recognition-based student attendance system using the CNN method, specifically optimized for Mataram Technology University. Unlike conventional approaches, this study addresses dataset limitations by applying data augmentation techniques and optimizing training parameters through different epoch variations. Additionally, the analysis of overfitting risks and the implementation of early stopping help improve the model's generalization capabilities. The findings of this research enhance the model's real-world applicability by ensuring its robustness against variations in lighting, facial angles, and conditions such as occlusion, which are crucial for implementation in educational.

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