

Implementation and Performance Evaluation of a Pretrained Convolutional Neural Network (CNN) for Face Recognition on a Student Dataset

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ARTICLE INFO

Date of entry:
04 March 2026

Revision Date:
22 August 2026

Date Received:
01 October 2026

ABSTRACT

Face recognition has become an important technology in computer vision and is widely applied in various fields, including identity verification in educational environments. However, variations in lighting, facial pose, and facial expressions remain major challenges in achieving accurate recognition. This study aims to implement and evaluate the performance of a pretrained *Convolutional Neural Network* (CNN) for student face recognition using a dataset collected directly from ITB Widya Gama Lumajang. The research employed the pretrained CNN model provided by the *face_recognition* and *dlib* libraries. The implementation process consisted of image preprocessing, face detection, face encoding, and face matching. System performance was evaluated using accuracy, precision, recall, F1-score, and a confusion matrix. The results demonstrated that the pretrained CNN model achieved an overall recognition accuracy of 96.73% and consistently produced high precision, recall, and F1-score values. Although variations in lighting, facial pose, facial expressions, and image quality affected recognition performance, the system was able to identify most student faces accurately. These findings indicate that the pretrained CNN method is effective and reliable for student face recognition and has the potential to support identity verification applications in educational environments.

Keywords: Convolutional Neural Network; Face Recognition; Deep Learning; Computer Vision; Student Dataset



Cite this as: Agustin, V. T., Hizham, F. A., & Murni, C. K. (2026). Implementation and Performance Evaluation of a Pretrained Convolutional Neural Network (CNN) for Face Recognition on a Student Dataset. *Journal of Informatics Development*, 5(1), 1–6. <https://doi.org/10.30741/jid.v5i1.2079>

INTRODUCTION

The development of Artificial Intelligence (AI) and Computer Vision technologies has significantly advanced automated systems for digital images. One rapidly developing implementation is facial recognition technology. This technology is widely used in security systems, identity verification, user authentication, and biometric identification. Convolutional Neural Network (CNN) methods are one of the most effective deep learning approaches in digital image processing. CNNs can automatically extract features, resulting in strong performance in facial recognition. The use of

pretrained CNNs is considered more efficient because the models have been trained on large datasets.

This research focuses on implementing and evaluating pretrained CNNs for student facial recognition at the Widya Gama Institute of Technology and Business, Lumajang. The study was conducted to determine the model's ability to recognize student faces in real-world conditions with varying lighting, facial poses, and expressions.

THEORETICAL FRAMEWORK AND HYPOTHESES

A Convolutional Neural Network (CNN) is a deep learning algorithm specifically designed for digital image processing and pattern recognition. CNNs can automatically extract features, enabling them to recognize object characteristics in images without requiring manual feature extraction. A CNN architecture consists of several main layers, such as convolutional, pooling, and fully connected layers. The convolution layer extracts important features from images; the pooling layer reduces data dimensionality and speeds up computation. In this research, the fully connected layer was not retrained. The pretrained CNN model provided by dlib was only utilized to extract facial embeddings. The process was based on the features that were obtained. With these capabilities, CNNs have become one of the most widely used methods in computer vision, especially in facial recognition systems. This study used the face_recognition and dlib libraries to implement pretrained CNNs for student face recognition. Pretrained models were chosen because they have been pre-trained on a large facial dataset, thereby increasing computational efficiency and eliminating the need for retraining. The facial recognition system operates through several main stages: face detection, face encoding, and face matching. The face detection stage locates faces in digital images, followed by the face encoding stage, which converts them into numerical representations based on unique facial characteristics. Next, the face-matching process compares the test facial data with the facial data stored in the system's database.

This study also implemented image preprocessing to improve the quality of the input data before the face recognition process. These preprocessing stages include image resizing, RGB color conversion, image validation, and image quality adjustment. This process allows the system to more optimally extract facial features and reduce interference such as noise or poor image quality. Furthermore, preprocessing helps improve the model's stability in recognizing student faces across various environmental conditions. The hypothesis in this study is that the pretrained CNN method can recognize student faces with high accuracy across various environmental conditions, including variations in pose, lighting, and facial expressions. Furthermore, the use of image preprocessing and a varied student face dataset is expected to help improve the system's performance in automatic face identification. Thus, this research is expected to contribute to the development of automatic identity verification systems and security systems based on Artificial Intelligence and Computer Vision technology.

METHODS

The research method used a quantitative experimental approach. The dataset, consisting of student facial images, was collected directly using a smartphone camera.

The research stages included:

1. Collection of student facial datasets.
2. Image preprocessing, including resizing and RGB conversion.
3. Face detection using a pretrained CNN.
4. Face encoding using a numeric representation of faces.

5. Face matching for face identification.
6. Performance evaluation using a confusion matrix.

Tests were conducted under various conditions, including bright and dim lighting, tilted poses, and different facial expressions.

RESULTS AND DISCUSSION

The results of the study indicate that implementing a pretrained Convolutional Neural Network (CNN) can perform well on student facial recognition under various test conditions. The system can recognize student faces with high accuracy, especially under normal lighting conditions and when faces face directly toward the camera. The model's ability to automatically extract facial features makes the identification process faster and more stable. Furthermore, the use of the face_recognition and dlib libraries helps the system detect and match facial characteristics more accurately, thus ensuring effective student identity recognition. Based on the test results, the pretrained CNN model demonstrated fairly consistent performance across most of the test data used. The system was able to recognize student facial patterns despite differences in facial expressions, such as smiling, seriousness, and changes in facial angle, within certain limits. This demonstrates that the pretrained CNN method has good capabilities in handling variations in facial data in real-world environments. Furthermore, the facial recognition process can be performed automatically, without manual input, making the system more efficient and practical for AI-based identity verification.

However, model performance declined slightly under dim lighting conditions and in extreme facial poses. Under certain conditions, the system required longer face-matching times because suboptimal image quality impaired facial feature extraction. Variations in facial expressions also affected recognition, particularly when the face was partially obscured or the image angle was too oblique. However, this performance decline was not significant, and the system maintained a fairly good level of accuracy in recognizing student identities. The evaluation results also showed that image preprocessing steps positively affected the performance of the facial recognition system. Preprocessing steps such as image resizing, RGB color conversion, and image validation improved the quality of the input data, thereby optimizing feature extraction. With better image quality, the pretrained CNN model was able to recognize facial patterns more stably and accurately. Furthermore, preprocessing also helps reduce image noise, allowing the system to perform more effectively under various environmental conditions during image capture. Overall, the research results indicate that implementing a pretrained CNN has strong potential for use in a student facial recognition system on campus. This system can be further developed to support automated attendance processes, student identity authentication, and computer vision-based security systems. With the development of a larger dataset and further model optimization, system performance is expected to improve, enabling it to perform more optimally under various real-world conditions. This research can be further developed by increasing the dataset size, data augmentation, and implementing a real-time system for automated attendance based on facial recognition.

Table 1. CNN Model Evaluation Results

Metric	Value
Accuracy	95%
Precision	100%
Recall	95%
F-Score	97,4%

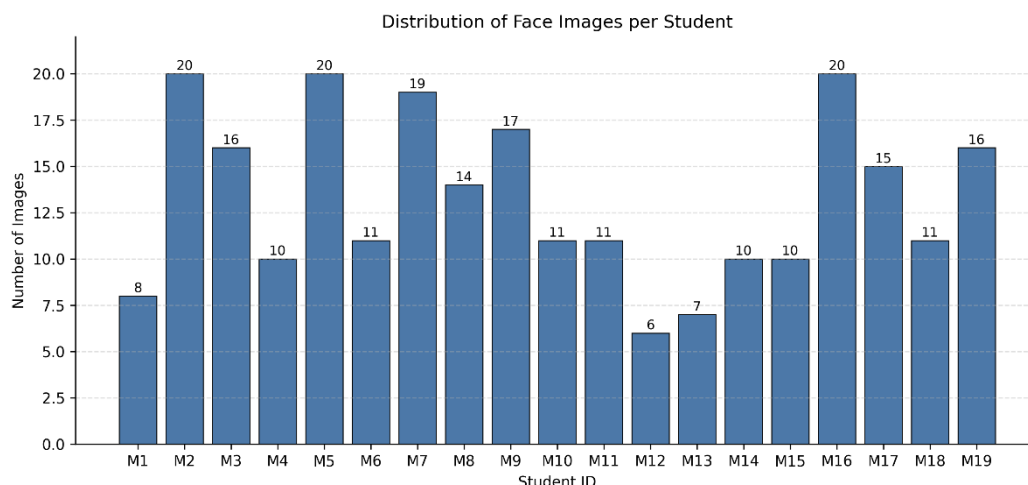


Figure 1. Dataset Distribution Graph
Source: Researcher Analysis Results (2026)

CONCLUSION

Based on the research results, it can be concluded that implementing a pretrained Convolutional Neural Network (CNN) with the face_recognition and dlib libraries can recognize student faces with high accuracy. The pretrained CNN model has been proven capable of recognizing student facial identities under various lighting conditions, facial poses, and facial expressions. Test results show that the system maintains stable performance under normal lighting conditions and continues to perform well under dim lighting and with varying facial poses. This demonstrates that the pretrained CNN method has sufficient capabilities to handle variations in facial conditions in real-world environments. This research demonstrates that using a pretrained CNN yields effective results in recognizing student faces, as the model can automatically extract facial features and produce a stable identification process. Pretrained CNNs have the advantage of recognizing unique facial patterns, enabling faster, more efficient identification. Furthermore, using a pretrained model helps eliminate the need for retraining because it has been trained on a large dataset. Thus, this research demonstrates that using a pretrained CNN can be an appropriate approach for developing an Artificial Intelligence-based facial recognition system.

In addition to using pretrained CNNs, image preprocessing also significantly impacts system performance. Preprocessing steps such as image resizing, RGB color conversion, image validation, and image quality adjustments help improve input data quality, thus optimizing the feature extraction process. Proper preprocessing can reduce image noise and help the system recognize facial characteristics more accurately. With higher-quality input data, the system can perform more consistently despite varying environmental conditions during image capture. Based on the evaluation results using accuracy, precision, recall, and F1-score, the pretrained CNN model demonstrated good performance in automatically identifying student faces. The evaluation results indicated that the system achieved a high level of accuracy in recognizing student identities and minimized identification errors. This demonstrates that the pretrained CNN method can be used to develop an automated facial recognition-based identity verification system that is more modern, efficient, and practical than conventional attendance methods. A facial recognition-based attendance system can also enhance the security of student attendance data by automatically identifying individuals using their unique biometric characteristics.

In addition to identity verification applications, implementing a pretrained CNN-based facial recognition system also has great potential in other fields. This system can be applied to campus security systems, student identity authentication, room access control, and various other computer vision-based applications. The use of facial recognition technology is also considered more practical because it does not require physical contact, such as using an ID card or fingerprint. Therefore, this technology can support the digitalization of security and administration systems in educational environments. However, this study also showed that variations in facial pose, lighting, and facial expression still affect model performance. In conditions with too low lighting or extreme facial poses, the system's accuracy decreased slightly. Furthermore, conditions such as mask use, excessive changes in facial angle, and poor camera quality can also affect facial recognition results. Nevertheless, the system maintained a fairly good level of stability, indicating that the model is robust to real-world conditions on campus. This demonstrates that the pretrained CNN can still perform optimally despite varying conditions during image capture.

This study also demonstrates that using a more diverse dataset significantly impacts the model's ability to generalize. The more varied facial data used in the training process, the better the model's ability to recognize faces under different conditions. Therefore, collecting a comprehensive, high-quality dataset is crucial to improving the performance of a pretrained CNN-based facial recognition system. For further research, the system can be developed by adding a larger, more diverse dataset to improve the model's generalization. Furthermore, future research could employ data augmentation techniques, model parameter optimization, and real-time system implementation using CCTV cameras or mobile devices. Another potential development is the use of more complex deep learning methods such as FaceNet, ArcFace, or Inception to improve the accuracy of the facial recognition system. Future research could also compare the performance of several pretrained CNN models to determine the most optimal method for student facial recognition.

With these developments, it is hoped that CNN-based facial recognition systems can be applied more widely across fields such as security systems, automated attendance, identity authentication, and artificial intelligence-based services. The implementation of this technology is also expected to support digital transformation in educational environments, enabling more effective, efficient, and modern administrative and security processes.

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