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# Optimizing KNN for Face Recognition and Location Detection in Mobile Employee Attendance Systems Using Machine Learning

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**Abstract:** Employee attendance is critical to company operations, particularly for firms involved in ATM installations collaborating with banks. An effective attendance system enables bank vendors to verify the completion of ATM installations. The current attendance method employed by the company requires employees to send photos of themselves with the installed ATM, including the machine number and installation location. The company's admin then compiles these photos into a summary that serves as proof of employee attendance and job completion, which is subsequently sent to the bank vendor. However, this method fails to accurately verify the employees' physical presence at the installation sites, raising significant concerns about the validity of attendance data. This lack of accuracy in attendance data affects performance evaluations, vendor trust and satisfaction, and the company's operational integrity. A facial recognition attendance system using the K-Nearest Neighbors (K-NN) method was proposed to address these issues. The K-NN method was selected for its effectiveness in classifying data based on proximity characteristics, making it ideal for precise attendance verification based on location and time. Test results demonstrated that the system achieved a 100% success rate in distance detection, 96.4% in position detection, and 50% in accessory usage detection. This system enhances the efficiency and accuracy of the employee attendance process.

**Keywords:** Face Recognition, K-Nearest Neighbor, Employee Attendance, Location Detection

## Introduction

Attendance is an activity of data collection to determine the number of people present at an activity in an institution or company (Kurnia Aji *et al*., 2023). Attendance is data collection used as evidence of employee attendance at work (Kusumo *et al*., 2022). Especially in companies, attendance systems are essential for assessing employee attendance and discipline (Shahab and Sarno, 2020). Each institution has its own system for recording attendance. One of the systems used for attendance is face recognition (Mubarak Alburaiki *et al*., 2021; Rastogi *et al*., 2023; Song and Chen, 2024). The research location in this study uses face recognition for attendance. The research location in this study uses face recognition for attendance. Employee attendance is crucial for companies engaged in ATM installation and collaboration with banks. Attendance for ATM installation within the city can still be managed by coming directly to the office for check-in and check-out attendance. However, if the ATM installation is done out of town, it becomes a problem for the company as attendance cannot be managed by coming directly to the office. The current attendance system for employees installing ATMs out of town requires them to send a photo of themselves with the installed ATM, including the machine number and location. The admin will compile the photos sent into a report to verify employee attendance and task completion, which will then be sent to the bank vendor. However, this method does not provide accurate verification of the employee's physical presence at the location, causing issues with the validity of attendance data for performance assessment by the bank. This inaccuracy not only affects performance evaluation but also impacts the trust and satisfaction of the vendor, as well as operational integrity.

Face recognition is a biometric technology widely applied in security systems alongside retina, fingerprint and iris recognition. Facial recognition is one of the image-processing-based technologies that uses some or all parts of the face for the authentication process, thereby enhancing the system's security level. This application uses a camera to capture a person's face, which is then compared with faces previously stored in a specific database.

The working mechanism of face detection involves analyzing a given image to detect if a face is present. If a face is detected, the system then determines the location and size of the face in the image. The principle of face recognition is that if face detection confirms the presence of a face, the system will compare it with facial images previously stored in the database.

Based on the background and problems mentioned above, developing an Attendance System with Face Recognition using the K-Nearest Neighbors (KNN) method is proposed to monitor employee attendance at various locations. K-Nearest Neighbors (KNN) is a method that uses a supervised algorithm to classify new objects. Developing a face recognition attendance application using the Nearest Neighbors (K-NN) method, which effectively classifies data based on proximity, ensures more accurate attendance verification based on location and time data.

Research related to face recognition was conducted by Ab Wahab *et al.* (2022) on the web-based online attendance system for employees at the University College of Yayasan Pahang (UCYP), then by Jha *et al.* (2023); Pooja *et al.* (2023) automatic attendance system with face detection and recognition with LBPH, next, the attendance information system using the Viola-Jones algorithm was conducted by Gavriell *et al.* (2021); Aparna *et al.* (2022). Then (Hasta Yanto *et al.*, 2022) researched attendance using face recognition and location detection. End then (Hate, 2019) developing student facial recognition applications.

This research introduces an innovative mobile-based employee attendance system utilizing facial recognition technology with the K-Nearest Neighbor (KNN) Algorithm. The novelty of this research lies in applying the simple yet effective KNN algorithm, which has been adapted to work on mobile platforms with limited resources. This system offers convenience and flexibility for employees to record their attendance from various locations and improves accuracy and efficiency compared to traditional attendance methods. Furthermore, this research highlights the importance of the security and privacy of employees' biometric data, ensuring that sensitive information is well protected. The implementation of this system shows great potential in reducing attendance fraud and enhancing time management for employees across various institutions.

## Materials and Methods

Face Recognition is a biometric technology used to identify or recognize an individual based on specific characteristics (Berle, 2020). The stages of face recognition can be seen in Fig. (1).

The stages of face identification in this system are divided into two main parts: Training and testing. The process begins with collecting input data in the form of facial images. During the preprocessing stage, these face images undergo several adjustments to enhance image quality and consistency, such as converting to grayscale, normalizing lighting, and cropping to focus on the facial area. Next, in the feature extraction stage, the Histogram of Oriented Gradients (HOG) method extracts essential features from the facial images. HOG works by calculating the distribution of gradients or changes in intensity in the image, which are then represented in a histogram. These features describe the facial structure and texture used as input for the next stage.

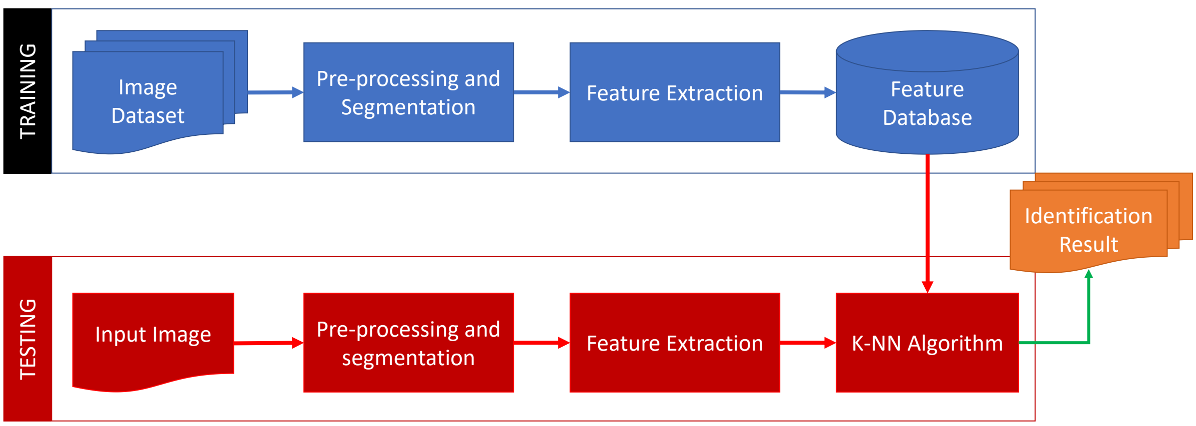


**Fig. 1:** Stage of face recognition

In the training stage, the features extracted from many labeled face images are used to train the K-Nearest Neighbor (K-NN) algorithm. KNN operates by storing all the training examples and classifying new data based on its similarity to the training data. In this case, similarity is measured by calculating the Euclidean distance between the features of the new facial image and the features of the facial images in the training dataset.

In the testing stage, the facial image to be identified first undergoes preprocessing and feature extraction using HOG, just as in the training stage. The extracted features are then compared with the features in the training dataset using the K-NN algorithm. The K-NN algorithm searches for the k-nearest neighbors based on the shortest distance in the feature space and determines the identity of the face based on the majority label of these nearest neighbors.

The result of this identification process is the predicted identity of the face from the input image, which includes information on whether the face matches any of the faces in the training dataset and an estimation of the accuracy of this prediction. With this system, the facial identification process becomes more accurate and reliable, enhancing the validity of attendance data and increasing vendor confidence in the company's attendance system.

### *Image Dataset*

In this process, a dataset of face images is collected to train the model. This dataset must consist of facial images represented by feature vectors or relevant facial characteristics that can distinguish one face from another. The data used in this research consists of 25 face images. The data collection process utilizes a webcam camera.

### *Preprocessing and Segmentation*

This stage is for enhancing the image quality or enhancement so that the image becomes more manageable, more effective, and faster to process in the subsequent stages. Preprocessing is one of the stages in face recognition where face image data undergoes processes such as cropping, face detection, resizing, and converting the format from RGB to grayscale. The purpose of the preprocessing stage is to ensure that face images can be processed more effectively and to increase the system's likelihood of successfully recognizing faces in a short amount of time.

### *Feature Extraction*

Feature extraction is the process of extracting the characteristics of an object that describe its attributes and distinguish it from every facial image in the dataset (database). Feature extraction is the stage of extracting features from the image, which are used as 'distinguishers' of the image. Image features include contours, shapes, colors, textures, etc.

### *Feature Database*

The dataset used in this research consists of face photos taken directly from a webcam. Each face was captured 50 times, consisting of 25 colored images and 25 grayscale images with a size of 108×108 pixels. Each image is labeled in the directory with an Employee Identification Number (EIP) for each face to represent the Employee Identification Number (EIP) of each individual associated with the face.

### *K-NN Algorithm*

Machine learning algorithms are applied to the training data and a suitable model for the data is found. The model is generated using specific machine learning techniques to discover correlations and patterns in the data obtained from the data preprocessing and feature extraction stages. The Algorithm that will be used in this research is the K-NN.

The K-nearest neighbor algorithm is a classification algorithm method based on the similarity level calculated by the nearest distance from its learning or training data and test data (Boiculese *et al*., 2013). The K-NN algorithm is one of the simplest machine-learning methods to implement without parameters (Wenguang and Shengxiong, 2023). The Euclidean distance method is the most commonly used method by researchers to calculate the distance in the K-NN algorithm.

The K-nearest neighbor algorithm is a classification algorithm method that works based on the similarity level calculated by the nearest distance from its learning data or training data and test data (Boiculese *et al*., 2013).

Euclidean distance is a process used to determine the distance between training and test image data in a system using Euclidean distance. The formula for calculating Euclidean distance is as follows (Munazhif *et al*., 2023; Wijati *et al*., 2024):

$$d(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \quad (1)$$

In the formula, $x_i$ and $y_i$ represent the elements of the face encoding vectors from the training data and the test data. The summation is performed from $I = 1\text{-}n$, representing the face vectors' dimensions. The square root of this sum gives the distance value between the two face vectors.

### *Identification Result*

The face identification result will mark the face in the input image with a box. It will be detected if the input image matches an already stored image. It will not be detected if the input image does not match any stored image.

### *Testing Design*

The testing design to be used in this research includes testing for accuracy, precision, and recall, as well as tests for image capture distance, position, and accessories.

Nine images will be used for accuracy, precision, and recall testing. In the distance testing, the distance between the face image and the webcam will be 30, 50, 100, and 200 cm. Position testing will involve capturing face images with the webcam in various positions: Front-facing, looking up and down at 30°, turning right and left at 90°, and tilting right and left at 45°. Face images will be captured with the webcam while wearing glasses and face masks for accessory testing.

## Results and Discussion

### *Data Preprocessing*

The data used in this research consists of 25 face images. The data collection process utilizes a webcam camera.

Before proceeding with face recognition, the dataset undergoes a preprocessing stage to enhance image quality and optimize computational efficiency. This research implements three main preprocessing steps: grayscale conversion, cropping, and resizing. These steps ensure that the images are in a uniform format, reducing noise and improving the accuracy of subsequent processing.

The first step in preprocessing is converting the captured images to grayscale. This transformation simplifies the image data by removing color information while preserving essential facial structures. Grayscale images are beneficial in face recognition tasks as they reduce computational complexity without significantly affecting recognition performance. In this research, 25 grayscale face images were produced, providing a consistent dataset for further processing. Figure (2) presents some sample grayscale images demonstrating the effectiveness of this transformation.

Once the images are converted to grayscale, they undergo a cropping process to extract only the relevant facial regions. This step eliminates unnecessary background elements, ensuring that the model focuses solely on the detected face area. The cropping process is particularly crucial for improving face detection accuracy and reducing processing time. By narrowing down the region of interest, the model can efficiently analyze facial features without interference from external objects. Figure (3) illustrates several examples of cropped images, highlighting the effectiveness of this approach.

After cropping, the images are resized to optimize memory usage and speed up recognition. In this study, each image is scaled down from an original resolution of 216×216 pixels to 108×108 pixels. This size reduction significantly decreases the computational load while maintaining sufficient detail for accurate face recognition. By resizing the images, the model can process multiple face samples more efficiently without compromising detection accuracy.

**Fig. 2:** Image grayscaling from RGB-image (left) into grayscale-image (right)

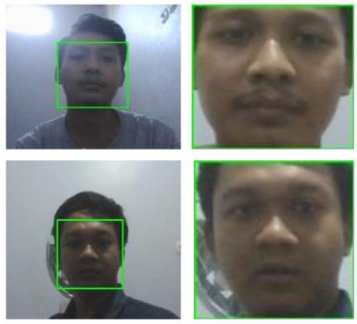

**Fig. 3:** Image cropping from original image (left) into face image (right)

### *Feature Extraction*

Following preprocessing, feature extraction is performed to identify and encode distinguishing facial characteristics. This phase comprises three main stages: face detection, face alignment, and face encoding. These steps collectively transform raw images into structured numerical representations suitable for machine learning algorithms.

Face detection is the initial step in feature extraction, where the system identifies and locates human faces within the given images. This research employs the face detection algorithm from the dlib library, which is based on the Histogram of Oriented Gradients (HOG) method. HOG effectively captures facial structures by analyzing pixel intensity variations, allowing the system to detect faces accurately. Once a face is detected, it is passed on to the next stage for further refinement.

After detecting a face, the alignment process ensures that all faces follow a consistent orientation, improving recognition accuracy. This is achieved by identifying key facial landmarks, such as the eyes, nose, and mouth, which serve as reference points for positioning the face. Using the shape_predictor_68_face_landmarks.dat model, 68 facial landmarks are detected and mapped onto the image, aligning the face to a standardized position. Figure (4) provides an example of this process, showcasing how facial landmarks are identified and utilized for alignment.

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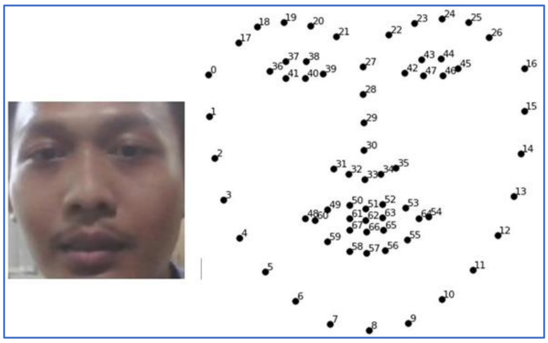

**Fig. 4:** Face alignment

Once the face is aligned, it undergoes the encoding process, transforming it into a numerical representation. This research utilizes the dlib_face_recognition_resnet_model_v1.dat model, which generates a 128-dimensional vector for each face. The model extracts unique facial features and converts them into mathematical data, making comparing and differentiating between individuals easier. This vectorized representation is crucial for facial recognition, enabling the system to analyze and classify faces efficiently. Figure (5) illustrates the encoding process, demonstrating how facial images are translated into structured data for further processing.

### *The Experiment Results*

This research conducted tests to evaluate the accuracy, precision, and recall of the K-Nearest Neighbor (KNN) method in predicting or identifying labels on test data. Additionally, tests were performed to evaluate each label's precision and recall levels individually and for distance variation, position variation, and accessory variation.

Table (1) presents a detailed evaluation of the classification model's performance, including precision, recall, F1-score, and support for each class. The model has demonstrated high accuracy, achieving an overall classification accuracy of 96%, indicating that most predictions were correct. The macro average and weighted average values for precision, recall, and F1-score are all above 0.96, confirming that the model performs consistently well across all categories.

**Table 1:** K-NN identification performance

| Class | Precision | Recall | F1-score |
|---|---|---|---|
| 201408 | 1.00 | 0.93 | 0.97 |
| 201409 | 1.00 | 0.93 | 0.97 |
| 201410 | 0.88 | 0.93 | 0.90 |
| 201411 | 1.00 | 1.00 | 1.00 |
| 201412 | 0.93 | 0.93 | 0.93 |
| 201413 | 0.88 | 1.00 | 0.94 |
| 201414 | 1.00 | 1.00 | 1.00 |
| 201415 | 1.00 | 1.00 | 1.00 |
| 201416 | 1.00 | 0.93 | 0.97 |
| Accuracy | | | 0.96 |
| Macro avg | 0.97 | 0.96 | 0.96 |
| Weighted avg | 0.97 | 0.96 | 0.96 |

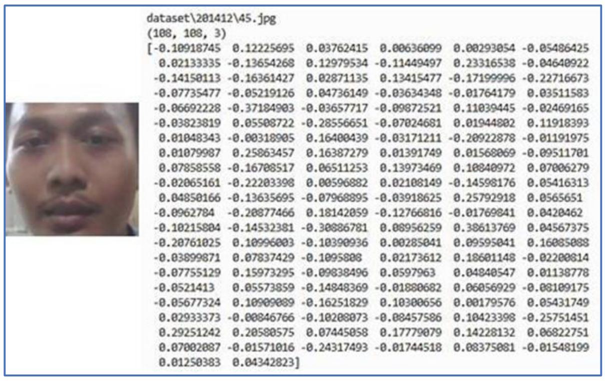


**Fig. 5:** Face encoding

Analyzing the class-wise performance, we observe that several classes, such as '201411', '201414', and '201415', achieved a perfect F1-score of 1.00, meaning the model correctly classified all instances without false positives or false negatives. Other classes, including '201408', '201409', and '201416', also show strong performance with an F1-score of 0.97. However, some classes, such as '201410', '201412', and '201413', exhibit slightly lower F1-scores, ranging from 0.90 to 0.94, which suggests minor misclassification cases. In these instances, the lower precision or recall values indicate that a few samples were either incorrectly classified or undetected.

Despite these minor variations, the model maintains a strong balance between precision and recall, which is reflected in its high F1-score across most classes. The consistency between the macro and weighted averages further indicates that the model performs well even when considering potential class imbalances. However, while these results are auspicious, ensuring that the dataset is sufficiently large and diverse is crucial to avoid overfitting. If the dataset is limited, applying data augmentation or cross-validation techniques could enhance the model's generalization capabilities, ensuring robustness when applied to new, unseen data.

### *Prototype Testing Results*

This research also conducted prototype testing of a face detection-based attendance model using three different scenarios: variations in distance, variations in position, and the use of facial accessories such as glasses. These scenarios were designed to evaluate the robustness and accuracy of the model under different real-world conditions, ensuring its reliability for practical applications.

In the distance variation scenario, the model was tested at four different distances: 30, 50, 100, and 200 cm. This test aimed to determine how well the face detection system could recognize individuals from varying distances. A shorter distance (30 cm) typically provides clearer facial details, whereas longer distances (100 and 200 cm) introduce challenges related to resolution and

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detection accuracy. By evaluating the model's performance at these distances, we can assess its ability to maintain recognition accuracy in different environments, such as close-range desktop usage and more expansive classroom or office settings. Figure (6) presents the results of prototype testing with variations in the respondent distance: 30, 50, 100, and 200 cm. The test results show that at all distance variations and all respondents, the system can identify faces correctly (100% correct).

The position variation scenario involved testing the model under different head orientations. The variations included 30-degree downward and upward tilts, 45-degree left and right tilts, and 90-degree left and right head turns. These variations were chosen to simulate natural movements, such as looking down at a document, slightly tilting the head, or turning to engage in a conversation. This scenario helps to evaluate the model's robustness in detecting faces under non-frontal angles, ensuring its effectiveness in real-world situations where users may not always face the camera directly. Prototype testing results with variations under different head orientations. The experiment results show that the system can identify faces correctly (100% correct) at all head orientations and all respondents.

Lastly, the facial accessories scenario tested the model's ability to recognize individuals wearing glasses. Since accessories like eyeglasses can alter facial features and create potential obstructions, this test helps to determine whether the system can accurately detect faces despite these changes. Successful recognition under this condition would indicate the model's adaptability to variations in facial appearance, making it more practical for diverse users.

The testing results with glasses as an accessory show that the 1st person was detected while the second person was not. However, when using a face mask as an accessory, neither the first person nor the second person is detected.

By conducting these three test scenarios, the study comprehensively evaluates the face detection-based attendance model. The results will help identify any limitations and potential improvements, ensuring the model is suitable for real-world applications where individuals may be at different distances, angles or wearing accessories.

### *Comparative Analysis*

Evaluating various methods based on performance and complexity trade-offs highlights K-Nearest Neighbor (KNN) as the most suitable choice for the proposed mobile employee attendance system (Table 2). KNN achieves an accuracy of 96.4%, outperforming CNN and equaling the accuracy of Transfer Learning and 3D Recognition methods. However, its advantage lies in its moderate computation time and relatively straightforward implementation, making it more practical for real-time applications than computationally intensive alternatives like CNN and 3D Recognition.

**Table 2:** Performance and complexity trade-offs

| Method | Accuracy (%) | Computation Time | Memory Requirements | Scalability |
|---|---|---|---|---|
| KNN | 96.4 | Moderate | High | Low |
| CNN (Nurkhamid et al., 2021) | 81.3 | High | Moderate | High |
| Transfer Learning (VGG) (Ali et al., 2024) | 95.0 | Low | Low | High |
| 3D Recognition (Dang, 2023) | 95.0 | High | High | Moderate |

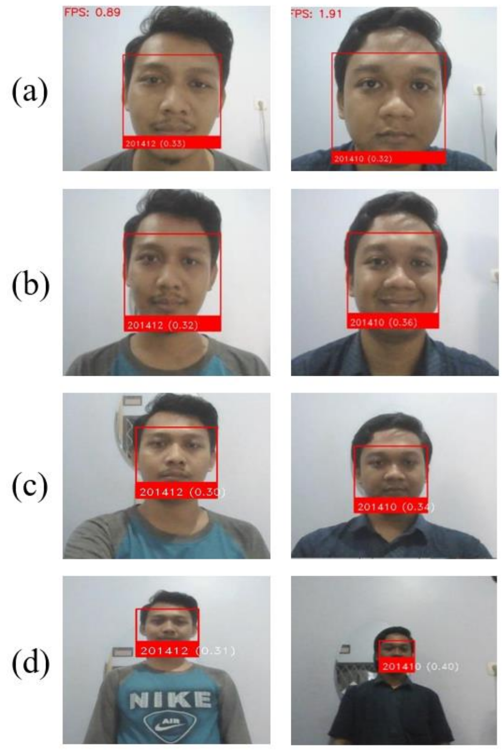


**Fig. 6:** Prototype testing with variations in respondent distance: (a) 30 cm, (b) 50 cm, (c) 100 cm, and (d) 200 cm

While Transfer Learning using pre-trained models such as VGG achieves a comparable accuracy of 95% with lower memory requirements and better scalability, it demands integration with more complex frameworks and higher initial training times, which may not align with the current system's objectives of simplicity and efficiency. Similarly, 3D Recognition, although highly accurate and capable of capturing depth features, involves substantial memory and computational overhead, making it less viable for mobile and lightweight applications.

KNN's trade-offs, such as its high memory requirements and low scalability, are mitigated by the modest size of the dataset and the system's specific application context, where the simplicity of implementation and moderate computational demands outweigh the need for high scalability. These factors make KNN an optimal balance between accuracy and resource utilization, offering a practical and efficient solution for face recognition in employee attendance verification systems.

### *Discussion*

The results of the experiments demonstrate the strengths and limitations of the K-Nearest Neighbor (KNN) algorithm in face recognition for mobile employee attendance systems. The overall performance of the KNN model was promising, achieving an accuracy of 96%, a precision of 97%, and a recall of 96%. These metrics reflect the model's effectiveness in accurately identifying faces, minimizing false positives, and reliably detecting target faces. This strong performance indicates that the model can provide accurate and efficient attendance verification, essential for practical applications.

In testing the model's robustness across various distances, the system achieved 100% accuracy for all tested distances of 30, 50, 100, and 200 cm for both individuals. These results highlight the model's ability to maintain consistent performance irrespective of spatial variations, making it well-suited for real-world applications where users' proximity to the device may vary.

However, the results were less consistent when evaluating positional variations. The system successfully recognized both individuals in most scenarios, such as front-facing, ±30° looking up, ±30° looking down, and tilting angles of ±45°. However, recognition performance declined for extreme angular deviations, such as ±90° turning to the side, where only one individual was correctly identified. This limitation suggests that while the KNN model is robust under moderate positional changes, its reliability diminishes with more extreme variations, potentially due to insufficient training data for such cases or the algorithm's inherent limitations in capturing complex facial geometry.

The accessory variation tests revealed significant challenges. When individuals wore glasses, the system detected only one of the two test subjects. When face masks were used, the system failed to recognize either individual. These findings highlight a critical limitation of the KNN algorithm in handling occlusions, a challenge exacerbated by the widespread use of masks in many real-world scenarios. The inability to accurately recognize partially obscured faces underscores the need for more sophisticated feature extraction techniques and advanced recognition models.

To address the computational inefficiency of KNN, particularly with larger datasets, dimensionality reduction techniques such as Principal Component Analysis (PCA) could be employed. However, transitioning to deep learning models would inherently address this challenge, as such models are better equipped to handle high-dimensional data. Future research could also explore multimodal biometric systems, combining facial recognition with other identifiers like voice or fingerprint data to enhance accuracy and robustness.

Overall, these findings and limitations point to several avenues for future research. These include the integration of GPS technology, the adoption of deep learning techniques for improved scalability and accuracy, the use of data augmentation to enhance accessory detection, and the exploration of multimodal biometric systems. Addressing these areas would significantly enhance the system's reliability, efficiency, and adaptability to real-world conditions.

## Conclusion

The model developed using the K-Nearest Neighbors (KNN) method for face classification demonstrated an accuracy rate of 97%, with a precision of 96% and a recall of 96%. This indicates that the model has a solid ability to recognize and classify faces with high accuracy. Implementing KNN in a mobile-based employee attendance system provides a significant solution to the problem of verifying physical presence at ATM installation sites. In addition to enhancing the validity of attendance data, this system supports more objective and transparent performance evaluations and strengthens the trust and satisfaction of the bank's vendors. Therefore, using the KNN method in the employee attendance system has proven to deliver reliable results in recording employee attendance, thereby improving the company's operational efficiency and the integrity of attendance data.

Future research is recommended to integrate GPS technology with the facial recognition-based attendance system. This integration will add an essential validation layer to ensure the presence of employees at the correct installation locations. By utilizing GPS data, the system can automatically match the physical location of employees with the scheduled installation locations, thus reducing the likelihood of fraud and improving attendance accuracy. Because of the potential limitation of using a small dataset and its implications for the model's generalization, we also plan to expand the dataset by including a broader range of facial images with varying lighting, poses, and accessories.

Additionally, greater attention should be given to data security and privacy aspects. Since facial data is sensitive information, research should focus on developing robust facial data encryption mechanisms and protection against potential misuse or data breaches. Implementing strict security standards and comprehensive privacy policies will help ensure that employee data is well-protected and increase user trust in the system. Therefore, the attendance system will become more accurate, reliable, secure, and trustworthy for all stakeholders.

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## Author's Contributions

**Painem:** Initiated research projects, developed the research conceptual frameworks, conducted data analysis and interpretation, and gave final approval of the version to be submitted and any revised versions.

**Hari Soetanto:** Drafted the article, reviewed the layout and grammar, and provided scientific input on the results.

**Achmad Solichin:** Assisted with the data acquisition process, set up experimental environments, developed model implementations, and helped analyze research findings.

**Ibnu Ramadhan:** Contributed to the technical development, provided expertise in implementing experimental models, and assisted in data analysis and interpretation.

## Ethics

The authors confirm that this manuscript has not been published elsewhere and that no ethical issues are involved.

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