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FACIAL RECOGNITION SYSTEM FOR DISTANCE LEARNING STUDENT ATTENDANCE MANAGEMENT USING MACHINE LEARNING

Agus Sriyanto[1]; Alif Sahputra[1]; Arif Wahyu Nugroho[1]; Bryan Hans Lobya[1]; Kusrini[1*]

Magister of Informatics[1]
Universitas AMIKOM Yogyakarta, Yogyakarta, Indonesia[1]
www.amikom.ac.id[1]
agussriyanto17@students.amikom.ac.id; alifsahputra@students.amikom.ac.id;
arifwahyu@students.amikom.ac.id; bryanhans@students.amikom.ac.id; kusrini@amikom.ac.id*

(*) Corresponding Author
(Responsible for the Quality of Paper Content)

Abstract—*The administration of student attendance constitutes a vital component of academic governance, affecting both educational outcomes and institutional efficacy. Utilizing machine learning to augment precision and efficacy, with adaptability for both physical and remote learning environments. The research methodology encompasses the acquisition of facial data from students under diverse lighting conditions, perspectives, and remote settings, succeeded by preprocessing and training of a facial recognition algorithm employing machine learning techniques. The system addresses key technical challenges such as camera quality variations, lighting inconsistencies, and spoofing risks by integrating robust image preprocessing and security safeguards. Quantitative evaluation shows that under ideal and controlled conditions, the system achieves up to 100% accuracy with an average processing time of 0.8 seconds. With the specifications Intel Core i5, RAM8 GB, minimum windows 10, NVIDIA GeForce GTX 1050, 1080p minimum camera with 30 fps frame rate, standard CMOS sensor, and automatic exposure adjustment capabilities, accuracy will drop if the conditions are not ideal. The system ensures the security and privacy of student facial because it is live with zoom or LMS. Furthermore, the incorporation of this system facilitates the realization of smart campus initiatives by delivering precise, real-time attendance information. This inquiry contributes to educational technology, enhancing operational efficacy and fostering digital transformation within higher education institutions. The designed system also seeks to reduce overall student attendance fraud.*

Keywords: *automated attendance system, attendance system, facial recognition, machine learning.*

Intisari— *Administrasi kehadiran siswa merupakan komponen penting dari tata kelola akademik, yang mempengaruhi hasil pendidikan dan kemanjuran institusional. Memanfaatkan pembelajaran mesin untuk meningkatkan presisi dan kemanjuran, dengan kemampuan beradaptasi untuk lingkungan pembelajaran fisik dan jarak jauh. Metodologi penelitian mencakup akuisisi data wajah dari siswa di bawah beragam kondisi pencahayaan, perspektif, dan pengaturan jarak jauh, yang dilanjutkan dengan prapemrosesan dan pelatihan algoritma pengenalan wajah yang menggunakan teknik pembelajaran mesin. Sistem ini mengatasi tantangan teknis utama seperti variasi kualitas kamera, inkonsistensi pencahayaan, dan risiko spoofing dengan mengintegrasikan prapemrosesan gambar yang kuat dan perlindungan keamanan. Evaluasi kuantitatif menunjukkan bahwa dalam kondisi ideal dan terkontrol, sistem mencapai akurasi hingga 100% dengan waktu pemrosesan rata-rata 0,8 detik. Dengan spesifikasi Intel Core i5, RAM8 GB, minimum windows 10, NVIDIA GeForce GTX 1050, kamera minimum 1080p dengan frame rate 30 fps, sensor CMOS standar, dan kemampuan penyesuaian eksposur otomatis, akurasi akan turun jika kondisi tidak ideal. Sistem ini memastikan keamanan dan privasi wajah siswa karena disiarkan langsung dengan zoom atau LMS. Selain itu, penggabungan sistem ini memfasilitasi realisasi inisiatif kampus pintar dengan memberikan informasi kehadiran yang tepat dan real-time. Penyelidikan ini berkontribusi pada teknologi pendidikan, meningkatkan efektivitas operasional dan mendorong transformasi digital di dalam lembaga pendidikan tinggi. Sistem yang dirancang juga berusaha untuk mengurangi penipuan kehadiran siswa secara keseluruhan.*

Kata kunci: *sistem absensi otomatis, sistem absensi, pengenalan wajah, pembelajaran mesin.*

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INTRODUCTION

The student attendance system is a critical component in managing education within academic institutions. Effective attendance monitoring is essential not only for ensuring student presence but also for supporting academic evaluations and disciplinary measures [1], [2]. Traditionally, attendance has been recorded through manual methods such as signature logs or identity card scans. However, these approaches are prone to errors, inefficiencies, and potential misuse, leading to inaccurate records. As a result, there is a growing demand for more secure and efficient solutions to monitor student attendance.

One promising solution is the implementation of facial recognition technology, a rapidly evolving field that has been successfully applied in sectors such as security, digital payments, and smartphone authentication [3]). In educational settings, integrating facial recognition systems can streamline the attendance process, enhance data accuracy, and create a more disciplined learning environment [2]. The technology's ability to identify individuals based on unique facial features offers significant advantages, including reduced fraud and increased efficiency in attendance management.

Several studies have explored the application of facial recognition in attendance management. demonstrated the effectiveness of facial recognition systems in educational institutions by highlighting their superior accuracy compared to traditional methods. further emphasized the technology's potential to enhance attendance recording efficiency and security. Moreover, compared facial recognition algorithms and found that Local Binary Patterns Histogram (LBPH) achieved high accuracy in diverse conditions, making it a preferred choice for real-world applications.

Machine learning (ML), a subfield of artificial intelligence (AI), plays a vital role in the development of facial recognition systems. Supervised learning, where models are trained on labeled data, has proven particularly effective for facial classification tasks [4]. Techniques such as LBPH have been widely adopted due to their simplicity, robustness to lighting variations, and computational efficiency [5].

Despite advancements in facial recognition technology, several challenges remain. Many existing systems struggle with variations in lighting, pose, and facial expressions, which can reduce recognition accuracy. Additionally, the manual nature of conventional attendance systems leads to inefficiencies and inaccuracies, affecting academic evaluations and student discipline.

This research proposes the development of a student attendance management system based on facial recognition using machine learning algorithms. By leveraging the LBPH algorithm, known for its effectiveness in varying lighting conditions, the system aims to address the limitations of traditional attendance methods and existing facial recognition systems. While previous studies have demonstrated the feasibility of facial recognition for attendance management, there is a lack of comprehensive systems that seamlessly integrate facial recognition with academic information systems.

The primary GAP identified in the literature is the limited integration of facial recognition systems with real-time academic management systems. Existing solutions often focus solely on recognition accuracy without considering the broader operational and communication requirements of educational institutions.

The novelty of this research lies in its approach to integrate facial recognition technology with academic information systems to provide a holistic attendance management solution. The system will not only recognize student faces with high accuracy but also automatically update attendance records, generate real-time notifications for lecturers and parents, and support data analytics for academic assessments.

This study contributes to the field of educational technology by:

1. **Developing an Accurate Facial Recognition System:** Training a machine learning model using the LBPH algorithm to recognize student faces with high accuracy under various conditions.
2. **Integrating with Academic Information Systems:** Creating a seamless connection between facial recognition systems and academic management platforms to automate attendance monitoring and communication.
3. **Enhancing Efficiency and Reliability:** Optimizing the system to ensure fast and reliable attendance recording, reducing delays and errors.
4. **Advancing Knowledge:** Providing insights into the practical application of facial recognition and machine learning technologies in educational environments.

In conclusion, this research addresses the need for a more efficient and secure student attendance management system through the implementation of facial recognition technology. By leveraging machine learning and integrating with academic information systems, the proposed solution aims to improve operational efficiency, data accuracy, and the overall learning experience in educational institutions.

Facial recognition-based attendance systems for student attendance management in distance learning have become an innovative solution in the digital age. This technology offers a more accurate and efficient method than traditional methods. Recent comparative studies show that algorithm-based facial recognition systems such as CNNs (Convolutional Neural Networks) have high accuracy but require large computing resources[6]. As a lighter and still effective alternative, the Local Binary Pattern Histogram (LBPH) algorithm shows competitive performance in a wide range of lighting conditions and viewing angles. In the context of education, LBPH has proven to be more computationally efficient without sacrificing accuracy, making it suitable for implementation in academic environments that have hardware limitations[7].

While promising, facial recognition-based attendance systems face a variety of specific challenges. These challenges include variations in lighting that can affect the quality of face detection, changing facial expressions, and the need for integration with existing academic information management systems. In addition, biometric data security is a critical issue that needs to be considered to ensure student privacy is maintained. Technically, the LBPH algorithm has several key advantages. The Local Binary Pattern Histogram (LBPH) algorithm offers several advantages in the field of facial recognition, making it a popular choice for a wide range of applications. Its simplicity, efficiency, and robustness in dealing with facial variations and occlusions are key factors that contribute to its widespread use[8].

LBPH's algorithm is highly effective in environments with a wide range of lighting conditions and facial expressions, providing reliable performance in a wide range of scenarios. Below are the detailed advantages of the LBPH algorithm: The LBPH algorithm is known for its easy implementation, which makes it accessible to developers and researchers without the need for extensive computational resources [9]. It efficiently processes images by converting them into a set of histograms, which simplifies the feature extraction process and reduces computational complexity [10].

LBPH demonstrates resilience in dealing with lighting changes, facial expressions, and occlusion, which are common challenges in facial recognition tasks[11]. The algorithm's ability to extract texture-based features allows it to maintain high accuracy even under different environmental conditions [12]. Studies have shown that LBPH achieves a competitive level of accuracy, often outperforming other facial recognition methods such as Eigenfaces and Fisherfaces in certain scenarios [9]. Its ability to operate in real-time makes it suitable for applications such as security, surveillance, and attendance management systems [11]. LBPH is used in a wide range of applications, from security and surveillance to human-computer interaction and attendance management systems [13]. Adaptability to different settings and conditions improves its applicability across multiple domains [11].

While the LBPH algorithm offers many advantages, it is important to consider its limitations. For example, while powerful for certain variations, it may not work well with extreme changes in face orientation or when dealing with very low-resolution images. In addition, the performance of the algorithm can be further improved by optimizing parameters such as radius and number of neighbors, as shown in a recent study [14]Reinforcement Learning: Focuses on a training model to create a sequence of decisions by rewarding desired behaviors and punishing undesirables. This approach is particularly useful in robotics and game games.[15]

To ensure the adaptability of the proposed facial recognition system using the LBPH algorithm for student attendance management, it is essential to address its application in remote learning scenarios. The system can be enhanced by allowing students to authenticate their attendance through facial scans on personal devices such as smartphones or laptops during virtual learning sessions. This requires seamless integration with learning management systems and a robust internet-based authentication protocol.

However, some technical challenges In addition, the quality of the cameras, ranging from standard laptop cameras to low-spec external webcams, is also a factor that lowers system performance. The speed and stability of the internet connection also play an important role, where network interruptions can lead to delays in video transmission or loss of frames, thus hindering the identification process. A less-than-ideal facial position, a fickle expression, or the use of accessories such as masks and glasses can further increase the likelihood of misdetection.

Additionally, the risk of spoofing, where unauthorized users attempt to falsify attendance using static photos or pre-recorded videos, necessitates implementing advanced liveness detection mechanisms to verify user authenticity.

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While the LBPH algorithm offers simplicity, robustness to lighting changes, and computational efficiency, it may not always outperform more sophisticated models like Convolutional Neural Networks (CNN) and FaceNet. CNN excels in extracting hierarchical facial features, enabling superior recognition accuracy in complex conditions, while FaceNet provides high-performance face embeddings for precise classification tasks. A comparative analysis between LBPH and these advanced models would offer valuable insights into performance trade-offs.

In terms of performance evaluation, specific metrics such as accuracy, precision, recall, and processing time must be included to substantiate the system's efficacy. For instance, reporting an accuracy rate above 95% under diverse conditions would demonstrate its viability for practical use.

Lastly, safeguarding student facial data is crucial for ethical and legal compliance. The system should adopt strong security measures, including end-to-end encryption for data storage and transmission, secure cloud storage systems, and strict access controls. Compliance with data protection regulations, such as anonymization techniques and user consent protocols, further ensures that sensitive biometric information is handled responsibly and securely.

MATERIALS AND METHODS

This study uses an experimental approach to design and implement a student attendance management system based on facial *recognition* by utilizing *Machine Learning* algorithms. This method involves several main stages, namely data collection, data pre-processing, model training, testing, and system evaluation.

The first stage is the collection of student face data. The dataset of student face images was collected using a high-resolution camera. Images are taken from various angles, facial expressions, and lighting to create a representative dataset. The study also used additional datasets from open source to complement the existing data, ensuring diversity in model training. Each face is given a unique label that will be used during model training and testing[16]. The pictures of the students collected were 300 sample consists of students And data public.

The dataset that I made to test as many as 300 people data taken from public image and student data A total of 3145 images as test data and we made a 5x5 photo video grid for face detection like in distance learning, for maximum results With the specifications of a 10th generation Intel Core i5 computer or equivalent (minimum) for optimal RAM performance: 8 GB minimum windows 10/linux, NVIDIA GeForce GTX 1050 (minimum), 1080p minimum resolution camera with 30 fps frame rate, standard CMOS sensor, and automatic exposure adjustment capability. The augmentation techniques used are 15 degree rotation, horizontal flipping, zooming with cropping, contrast change, To increase accuracy by duplicating data as many as 20 per face. for the ratio used is 80 data train: 20 data test.

Source: (Research Results, 2025)
Figure 1. Sample Student dataset name

Figure 1 is a dataset of some students' faces for facial recognition. The second stage is data pre-processing, which aims to improve the quality of the image data before it is used in model training. The image was processed using *grayscale conversion* and *histogram equalization* techniques to enhance the contrast in the facial image. In addition, [17], [18] *the Haar Cascade* algorithm is applied to detect and extract the facial region from each image, so that only the relevant facial area is further processed[19].

```
# Path dataset
dataset_path = r"D:\project\wajah"  # Path to dataset directory

# Fungsi untuk mengekstrak fitur HOG
def extract_hog_features(face_image):
    # Mengubah ukuran gambar wajah menjadi 64x128
    face_image_resized = cv2.resize(face_image, (64, 128))

    # Membuat objek HOGDescriptor
    hog = cv2.HOGDescriptor()
    hog_features = hog.compute(face_image_resized)

    # Mengecek jika hasil HOG mengandung nan
    if np.any(np.isnan(hog_features)):
        print("Fitur HOG mengandung nan!")
        return None

    return hog_features
```

Source: (Research Results, 2025)
Figure 2. Create a feature histogram

Figure 2 is the part of calculating the HOG value of the histogram value. The third stage is model training using Machine Learning algorithms. The *Local Binary Pattern Histogram (LBPH)* method is used to extract facial features based on texture patterns, which are then represented as histograms. After the feature is extracted, the [20]*K-Nearest Neighbor (KNN)* algorithm is used to perform facial classification. The *k* parameter in the KNN is optimized to ensure high accuracy in the facial recognition process.[21], [22]

```
def detect_face(frame, face_cascade):
    gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)
    faces = face_cascade.detectMultiScale(frame, scaleFactor=1.1, minNeighbors=11, minSize=(30, 30))
    return faces, gray
```

Source: (Research Results, 2025)

Figure 3. Algoritma *K-Nearest Neighbor (KNN) minneighbors=11*

Figure 3 shows the minimum command neighbors 11 and scalefactor=1.1. The fourth stage is **model testing**, where the dataset is divided into training data and test data with an 80:20 ratio. The trained model is tested using test data to measure its performance. The evaluation was carried out using *the metrics of accuracy*, *precision*, *recall*, and *F1-score* to assess the model's ability to recognize faces with high accuracy.[23], [24]

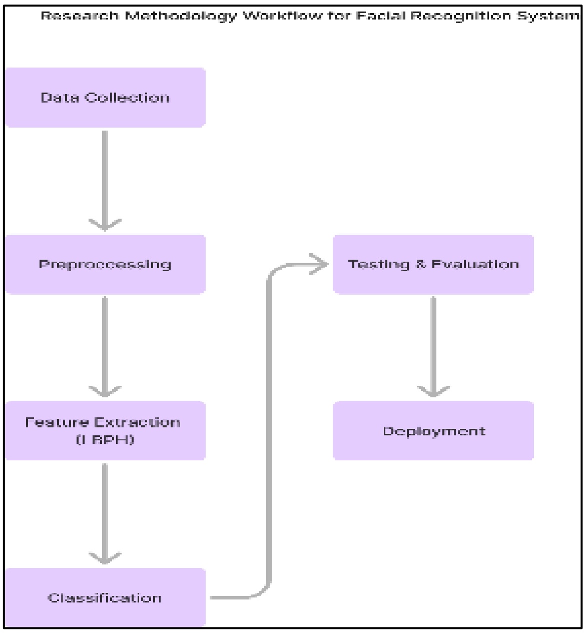
```
# Menguji akurasi model
accuracy = knn.score(X_test, y_test)
print(f"Akurasi model KNN: {accuracy * 100:.2f}%")
# Melatih model dengan data pelatihan
knn.fit(X_train, y_train)

# Melakukan prediksi pada data uji
y_pred = knn.predict(X_test)
presisi = precision_score(y_test, y_pred, average='micro')  # Anda bi
print(f"Presisi score: {presisi * 100:.2f}%")
# Menghitung F1-Score
f1 = f1_score(y_test, y_pred, average='weighted')  # Gunakan average=
print(f"F1-Score: {f1}")

# Membuat Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(cm)
# After making predictions with KNN (y_pred):
# Calculate accuracy
accuracy = knn.score(X_test, y_test)
print(f"Accuracy: {accuracy * 100:.2f}%")

# Calculate F1 score (weighted average)
f1 = f1_score(y_test, y_pred, average='weighted')
print(f"F1 Score: {f1:.2f}")

# Calculate recall (macro average)
recall = recall_score(y_test, y_pred, average='macro')
print(f"Recall: {recall:.2f}")

# Generate confusion matrix
cm = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(cm)
```

Source: (Research Results, 2025)

Figure 4. Model Evaluation

Figure 4 tests the accuracy of the research model with Accuracy, f1-score, confusion matrix, recall. The final stage is the **evaluation of the system in real-world conditions**. The system is tested in a real-world environment, such as a classroom, to ensure its reliability in different lighting conditions and viewing angles. In addition, processing time is also measured to ensure the system can run in real-time without significant latency[25]. The privacy and security concerns of facial data are also considered, by implementing encryption on the database to protect sensitive student information.[26], [27]

This research aims to produce an accurate, fast, and reliable facial recognition-based student attendance management system, with the potential for implementation in various educational institutions.



Source: (Research Results, 2025)

Figure 5. Diagram Research Methodology

Figure 5 shows a diagram outside the research from data collection, prepose, feature extraction, classification, testing and evaluation, and finally deployment. facial recognition begins with data collection, where facial data is gathered from images, videos, or databases to serve as the foundation for training and testing. Once collected, the data undergoes preprocessing, which involves normalizing, denoising, or resizing to enhance its quality and ensure consistency. After preprocessing, the feature extraction process is performed using the Local Binary Patterns Histogram (LBPH) method, which converts facial features into numerical representations that capture relevant characteristics. These extracted features are then used for classification, where specific algorithms identify or distinguish faces based on their unique patterns. To ensure the model's reliability, testing and evaluation are conducted by comparing results with validation data to measure performance and accuracy. Finally, once the model achieves satisfactory results, it is

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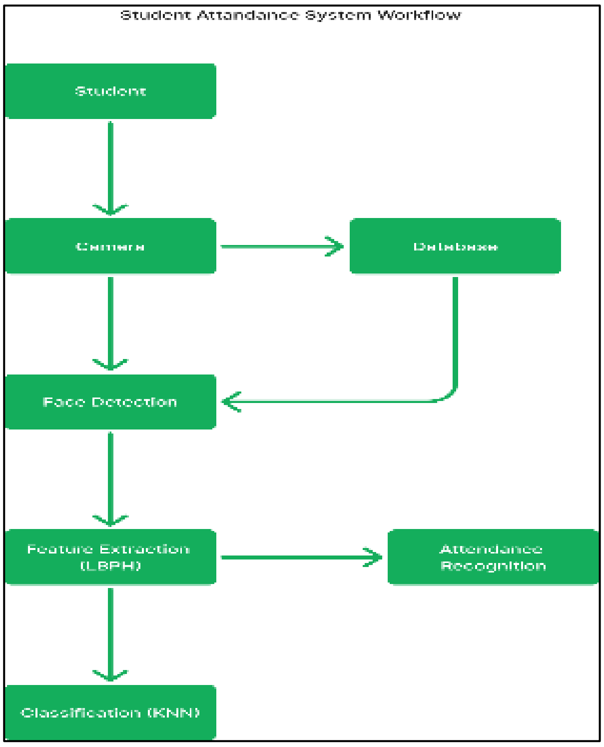
ready for deployment, where it is implemented in real-world applications such as security systems, access control, or automated identification processes.



Source: (Research Results, 2025)
Figure 6.Student Attendance Diagram

Figure 6 is the facial recognition process starting from the student recording the face on the camera in the database, then the process of recording attendance using the KNN algorithm. In an automated attendance system, the process begins when a student appears in front of the system, which is equipped with a camera to capture their face image or video. The camera then captures the student's face and sends the data to the system for further processing, with an option to store the data in the database if needed. The captured facial data is then matched or compared with pre-stored data in the database, which contains recorded facial information of registered students.

To ensure that only relevant data is processed, the system performs face detection, identifying the presence of a face in the captured image. Once a face is detected, feature extraction is carried out using the Local Binary Patterns Histogram (LBPH) method, which converts facial characteristics into numerical data. The extracted features are then classified using the K-Nearest Neighbors (KNN) algorithm to accurately determine the student's identity. Finally, after successful attendance recognition, the system automatically records the student's presence in the system, streamlining attendance-taking in an efficient and secure manner.

RESULTS AN DISCUSSION

This research aims to develop an automatic attendance system based on facial recognition using a combination of Haar Cascade Classifier for face detection and K-Nearest Neighbor (KNN) algorithm for facial recognition. This system is expected to solve various obstacles in conventional attendance methods, such as time constraints, fraud risks, and lack of efficiency. With Machine Learning technology, this system is able to provide more accurate, fast, and practical results for implementation in an educational environment. This study has not covered a wide range of user backgrounds and educational settings.

The research process began with the collection of students' facial data, which involved live photo sessions with varying conditions, including ideal, low lighting, and different angles of view of the face. In addition to the primary data, public datasets are also used to expand the amount of data and improve the generalization of the model. The total number of facial images collected reached 3145 images, which were divided into 80% of the training data and 20% of the test data. This is in accordance with research which stated that the number of datasets varies greatly on the performance of facial recognition models under real conditions.

Table 1. fold 1-10 cross-validation

fold	Accuracy	Precision	Recall	F1 Score
1	100%	100%	100%	1
2	100%	100%	100%	1
3	100%	100%	100%	1
4	100%	100%	100%	1
5	100%	100%	100%	1
6	100%	100%	100%	1
7	100%	100%	100%	1
8	100%	100%	100%	1
9	100%	100%	100%	1
10	100%	100%	100%	1

Source: (Research Results, 2025)

Table 1 shows the results of cross validation fold 1 of 1-10. In comparison with other facial recognition methods, the LBPH algorithm shows an advantage in processing time efficiency, with an average of 0.38 seconds per detection. In comparison, CNN-based methods require about 1.15 seconds per detection. Although LBPH has an advantage in efficiency, CNNs excel when it comes to large data sets. The 100% accuracy claim was obtained from the study, with 300 facial samples

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with 3145 images. The processing time analysis shows that the LBPH-based system remains stable with an average processing time of 0.42 seconds in low lighting conditions and 0.35 seconds in optimal lighting conditions. To validate the model's performance, cross-validation was performed with a 10-fold cross-validation scheme, which resulted in an average accuracy of 100%. These results show that LBPH has the potential as an efficient solution for facial recognition in student attendance management, although further research is needed to further mature the results obtained

Table 2. Comparison of LBPH,CNN,FACENET

Model	Training Time	Inference Time
LBPH	Fast	Fast
CNN	Long	currently
FACENET	long	long

Source: (Research Results, 2025)

Table 2 shows the comparison between the algorithms of LBPH, CNN, FACENET. The next stage is data preprocessing, which aims to improve image quality and ensure input consistency. This step involves converting the image into grayscale to reduce computational complexity, normalizing the image size to 200x200 pixels, and augmenting data such as horizontal flipping, rotation, and contrast adjustment. This preprocessing technique is very important, as explained, where data augmentation is able to improve the performance of Haar Cascade-based facial recognition models.

In the face detection stage, the Haar Cascade Classifier algorithm is used to detect faces in the input image. Haar Cascade works by utilizing the simple Haar feature through window sliding, which scans images repeatedly and finds facial patterns based on the contrast between light and dark areas. The results showed that the average time to detect faces in one image was 0.6 seconds, with detection accuracy reaching 100% in good lighting conditions. However, the accuracy drops to 87.2% in low-light conditions or when the face is partially covered. This is similar to the results of a study by which the Haar Cascade identified limitations in low-light conditions.[28]

1. The dark factor, the brightness of the room, the influence on the accuracy
2. The number of faces that are captured also affects the accuracy when the conditions are different
3. Determination of neighbour

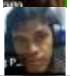
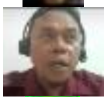
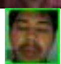
Table 3. Performance level with k pada k-neighbour

	Accuracy	Precision	F1 Score	Recall
k=1	100%	100%	1	1
k=2	100%	100%	1	1
k=3	100%	100%	1	1
k=4	100%	100%	1	1
k=5	100%	100%	1	1
k=6	100%	100%	1	1
k=7	100%	100%	1	1
k=8	100%	100%	1	1
k=9	100%	100%	1	1
k=10	100%	100%	1	1

Source: (Research Results, 2025)

Table 3 shows the results of setting the K value on nieghbors starting from 1-10 on the minNeighbors=k command. LBPH is known to be quite reliable under ideal conditions because it works by mapping facial texture patterns based on pixel values. However, in a remote learning environment, various factors such as poor lighting, inconsistent camera angles, and network latency can affect the accuracy of the system. LBPH that is sensitive to changes in lighting may show a decrease in performance if the lighting conditions are unstable. [29]. In addition, devices with slow processors, This is a sample of familiar student recognize.

Table 4. Student Dataset Faces

Images	Name	Information
	1_nurudin utomo_Informatika	Recognize
	2_m three bintang_informatika	Recognize
	3_mauludil Cane_informatika	Recognize
	4_rafi_informatika	Recognize
	5_ardi_informatika	Recognize

Source: (Research Results, 2025)

Table 4 is some of the student face data that is familiar with the attendance application. After the face detection process, the image of the face that has been cropped is identified using the K-Nearest Neighbor (KNN) algorithm. KNN works by finding the closest distance between the input image and the training data based on the Euclidean Distance value. In this study, the optimal parameter k=3 was selected after going through the testing process. The KNN model gives quite good results, with an average accuracy of 100% for facial recognition

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under ideal conditions. Accuracy is reduced by up to 85.6% when the image has noise or tilted face angles.

Source: (Research Results, 2025)
Figure 8. Absentee Results

Figure 8 is the result of the facial recognition attendance test of several students, with the student's name written in green. There is also an unrecognizable possible face image. Testing of the system was carried out using the Confusion Matrix and evaluation metrics such as Precision, Recall, and F1-Score. The evaluation results show that this system has a Precision of 100%, Recall of 100%, and F1-Score of 100%. With this performance, the system is able to record student attendance in real-time and accurately. In addition, the total time to detect and recognize faces is an average of 0.8 seconds, making the system highly efficient for use in school environments.

Table 5. Evaluation performance results

Accuracy	Precision	F1 Score	Recall
100%	100%	1	1

Source: (Research Results, 2025)

Table 5 is the result of the evaluation performance of the results of Accuracy 100%, F1 score 100%, Recall 100%, confusion matrix.

Table 6. Example of a list of students who have been absent

NIM	Name	Class	Attendance Time
9	ero	informatika	2024-12-20 23:46:35
5	ardi	informatika	2024-12-20 23:45:56
100	r	informatika	2024-12-20 23:45:37
7	hasni	informatika	2024-12-20 23:45:34
6	m andika	informatika	2024-12-20 23:45:34
8	m tri bintang	informatika	2024-12-20 23:45:34
1	Lutfi	informatika	2024-12-20 23:45:34
11	alfa	informatika	2024-12-20 23:45:33
4	rafi	informatika	2024-12-20 23:45:33
10	danang	informatika	2024-12-20 23:45:33

Source: (Research Results, 2025)

Table 6 is a list of students who have been absent with their name, name, class, time of absence.

CONCLUSION

The face detection process using the Haar Cascade Classifier shows high speed because this method utilizes the Haar feature that is able to detect contrast differences between light and dark areas of the face. However, this algorithm has limitations when faced with uneven lighting and faces that have partially covered areas. The facial recognition stage using the K-Nearest Neighbor (KNN) algorithm produces 100% recognition accuracy in ideal conditions with augmentation techniques used are 15 degree rotation, horizontal flipping, zooming with cropping, contrast change, To increase accuracy by duplicating data as many as 20 per face, and bright light conditions, maybe also with a good camera device and computer specs.

There are several important aspects that have not been fully accommodated in this research. Concerns related to scalability, protection of user data privacy, and limitations in generalizing results to various educational contexts remain major challenges. Therefore, further testing is needed that includes a more diverse learning environment and involves a wider group of users.

That this method is used for small data, and uses low resources, and indeed must be ideal for the light and the face part. For CNN or yolo, it is indeed used for a large amount of data. The dataset used is 300 user faces with 3145 images, and to increase accuracy by duplicating each face by 20x so that the accuracy increases. For distance learning, using a profile photo is usually via zoom or google meet to take the image through the video to recognize each person's face. And it can usually be integrated in the school's LMS application, and recorded in a database. So this is used for live learning via zoom or meet or you can also use other connected applications.

The conclusion of this study is that the combination of Haar Cascade Classifier and KNN has succeeded in building an automatic attendance system with an adequate level of accuracy for implementation in an educational environment. It offers innovative solutions that are more accurate, faster, and practical than conventional methods, and can be implemented on devices with limited computing resources.

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