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Research article

Development of a Real-Time Attendance System Based on Face Recognition Using the Viola-Jones Algorithm

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ABSTRACT

The development of computer vision technology is driving the transformation of attendance systems from conventional methods to biometric-based automated systems. Manual attendance systems still have weaknesses such as the potential for fraud, low efficiency, and difficulties in data management. This study aims to develop a face recognition-based attendance system that can work in real time using the Viola-Jones algorithm. The methods used include image conversion to grayscale, feature extraction using Haar Features, computational acceleration through integral image, and classification processes using AdaBoost and Cascade Classifier. The system is implemented using Python and the OpenCV library with a camera as the main input. Testing was carried out based on several parameters, namely face distance, lighting conditions, and face position relative to the camera. The results show that the system is able to detect and recognize faces in real time with a good level of accuracy under optimal lighting conditions and face positions, although it experiences a decrease in performance under low lighting conditions and extreme face angles. The conclusion of this study is that the Viola-Jones algorithm is effective for use in face recognition-based attendance systems with low computational requirements. The contribution of this research lies in the development of an attendance system that is efficient, practical, and able to minimize the potential for fraud compared to conventional methods.

1. INTRODUCTION

Advances in information technology, particularly in the field of computer vision, have driven the automation of various systems, including attendance systems[1], [2]. Attendance is a crucial component of human resource management as it relates to discipline, productivity, and performance evaluation. However, conventional attendance systems such as manual signatures or ID cards still suffer from various weaknesses, including susceptibility to data manipulation (such as leaving a timesheet), inefficiency, and time-consuming data recapitulation processes[3],[4]. Therefore, a biometric-based attendance system capable of operating automatically, accurately, and in real time is needed[5], [6]. One widely used approach is facial recognition, due to its contactless, practical nature, and ease of integration with camera devices[7], [8], [9].

Various studies have examined the application of facial recognition in attendance systems. Research by Jing et al and Tomar et al in their study "Deep Face Recognition: A Survey" shows that deep learning-based methods such as CNNs have high accuracy but require significant computing resources[10], [11]. Meanwhile, research by Gu et al. proposed the MTCNN method for face detection that is more robust to pose and lighting variations[12], [13]. On the other hand, classical methods such as the Viola-Jones method, introduced by Paul Viola and Michael Jones, are still widely used due to their advantages in detection speed and computational efficiency, especially for real-time applications with limited devices[14], [15].

Although deep learning methods offer high accuracy, their implementation is still limited to systems with high computing resources[16]. Conversely, the Viola-Jones method is more lightweight but has limitations when dealing with variations in lighting, facial angles, and complex environmental conditions[17], [18]. Furthermore, several previous studies have focused solely on the face detection aspect; not many have integrated the system comprehensively into real-time attendance applications tested under various operational conditions.

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Based on these issues, this study aims to develop a face recognition-based attendance system capable of operating in real time using the Viola-Jones algorithm. This study also evaluates system performance based on distance, lighting, and facial position parameters. The main contributions of this research are (1) the development of an efficient and practical face-based attendance system, (2) the implementation of the Viola-Jones method in a real-time environment with low computational requirements, and (3) a system performance analysis as a basis for further development towards a more robust and accurate system.

2. METHODS

This research employed an engineering research approach to develop a real-time attendance system based on face recognition using the Viola-Jones algorithm. The study consisted of several stages, including data collection, system design, implementation, and performance evaluation. The proposed system utilized a webcam as the input device to capture facial images, while the detection process was carried out using the Viola-Jones method with Haar Cascade Classifier. System testing was conducted under various conditions, including differences in lighting intensity, face distance, face position, and the use of facial attributes such as glasses and masks, to evaluate the performance and robustness of the proposed system.

2.1. Research Design

This research uses a systems engineering research approach with an experimental method. The focus of the research is to design, build, and test a real-time face recognition-based attendance system. The research process includes requirements analysis, system design, implementation, and system performance testing. Evaluation is conducted to measure the system's ability to detect and recognize faces under various environmental conditions.

2.2. Data and Data Sources

The data used is a facial image dataset obtained through direct capture using a webcam and stored as an internal dataset for system training and testing, as shown in Figure 1. The dataset consists of 500 facial images collected from 25 respondents, each with approximately 20 samples. Data were collected under various conditions, including lighting (bright, normal, dim), distance (30–100 cm), facial position (frontal and slightly tilted), and facial expression (neutral and smiling). Additionally, 100 non-facial images were used as negative data to support the classification process. All data was collected independently by the researchers and processed using OpenCV. This variation of dataset aims to test the system's ability to detect and recognize faces in real-time under various environmental conditions.

Figure 1. Dataset

2.3. Algorithm Used

The method used in this study is Viola-Jones, a commonly used algorithm for object detection and face recognition (Figure 2). This method was developed by Paul Viola and Michael Jones in 2001, using a machine learning approach to quickly distinguish between faces and non-faces. Viola-Jones works by utilizing Haar features arranged in a Cascade Classifier[19], [20]. The training process uses positive (face) and negative (non-face) data, enabling the resulting model to detect faces in new images. Although many modern methods have been developed, Viola-Jones remains effective and widely used due to its speed and efficiency in real-time applications.

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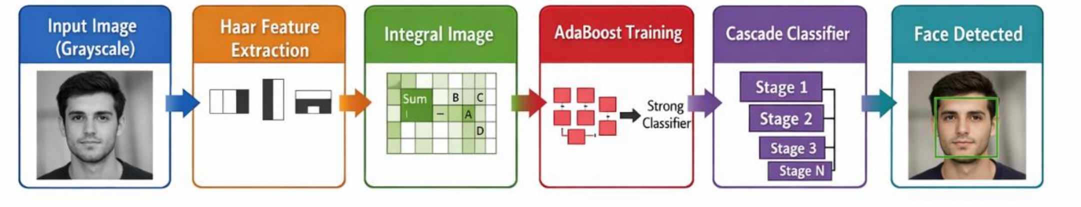


Figure 2. Viola-Jones Method

2.3.1. Grayscale Image

At this stage, the image is converted to grayscale, meaning that it contains only gray levels without color information, Figure 3. In the Viola-Jones method, grayscale is used as input because object detection relies heavily on differences in pixel intensity, not color. Using grayscale images has the advantage of reducing memory requirements and accelerating computational speed, allowing for more efficient face detection in real time.

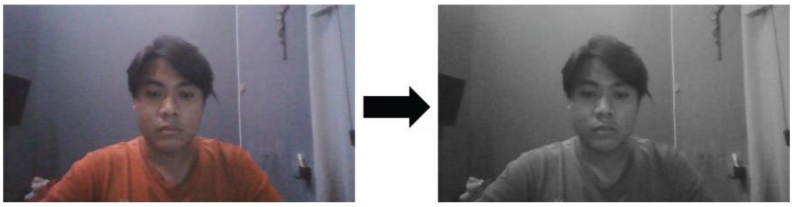
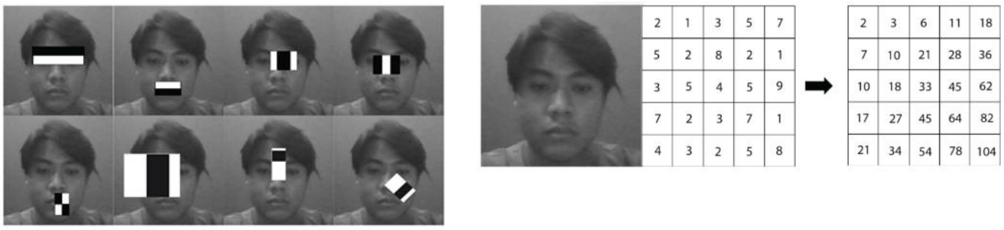


Figure 3. Grayscale Image

2.3.2. Haar Features

Haar features are visual features in the Viola-Jones method used to detect objects by calculating the difference in intensity between light and dark pixels, Figure 4. These features are capable of recognizing important facial patterns, such as differences in the eye and mouth areas. Haar features consist of square and line features, with variations such as three-level features for detecting more complex patterns. These features are tested at various scales and positions in the image, then combined in a cascade classifier to effectively distinguish target objects (faces) from non-target objects.



(a) (b)

Figure 4. (a) Haar Feature, and (b) Integral Image

2.3.3. Integral Image

Integral image is a technique in the Viola-Jones method used to accelerate Haar feature calculation (Figure 4b). This method works by storing the accumulated values of previous pixels, avoiding complex iterative calculations. Each pixel in the integral image represents the cumulative sum of the pixels above and to the left of it, allowing for faster and more efficient object detection.

2.3.4. Adaptive Boost

AdaBoost (Adaptive Boosting) is a machine learning method based on Viola-Jones that combines several weak classifiers into a strong classifier, Figure 5a. Each classifier is built from Haar features to distinguish positive and negative objects. Sample weights are adjusted at each iteration, with misclassified data being given greater weight to focus on in the next stage. This process is repeated until a more accurate model is produced. Thus, AdaBoost can improve object detection performance quickly and efficiently.

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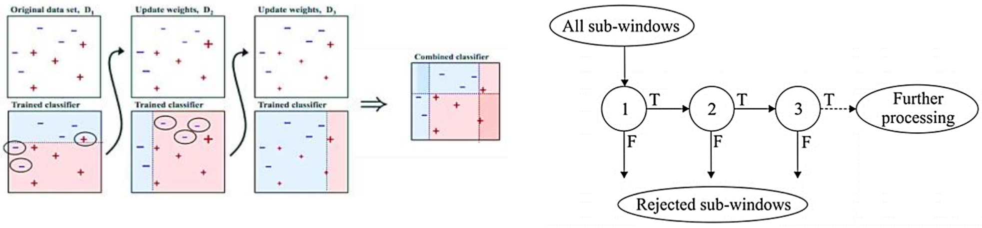


(a) (b)

Figure 5. (a) Adaptive Boost, and (b) Viola-Jones Structure

2.3.5. Haar Cascade Classifier

The Haar Cascade Classifier is a classification model based on the Viola-Jones method used for rapid face detection (Figure 5b). This model consists of several sequential classification stages (cascades) that utilize Haar features trained using AdaBoost with positive and negative data. Each stage quickly filters out areas containing no objects, while subsequent stages perform more detailed analysis of potential areas. This multi-stage approach makes the detection process more efficient and faster.

2.4. Research Methodology

This research process begins with system initialization, which involves activating the camera (webcam) to capture facial images in real time. Next, the system performs face detection using the Viola-Jones method, which consists of several stages: image conversion to grayscale, feature extraction using Haar-like features, calculating the integral image to accelerate the computational process, and classification using the AdaBoost method implemented in the Haar Cascade Classifier. Successfully detected faces are then compared to a dataset of faces stored in the database. This process aims to determine whether the face has been registered. If the face is identified in the dataset, the system will record the attendance and declare the attendance successful. Conversely, if the face is not registered, the system will output an error message. All valid attendance results are then automatically saved in a file, such as Excel, to facilitate data processing and reporting, Figure 6.

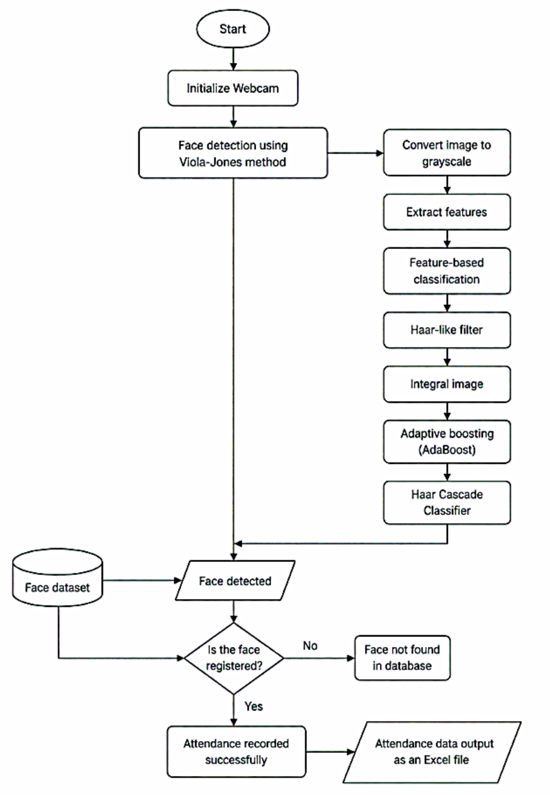


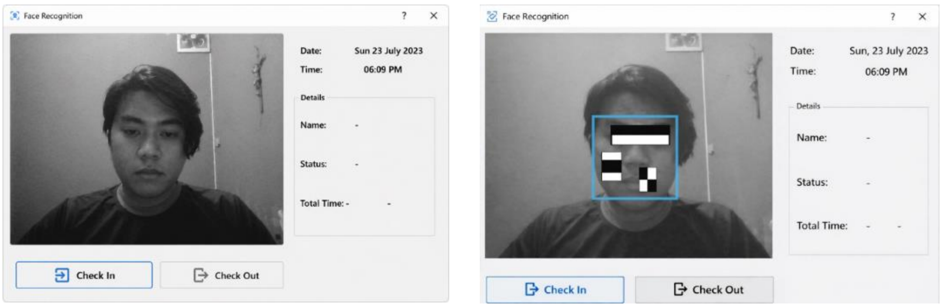
Figure 6. Research Methodology

3. RESULT

This section presents the implementation and testing results of the proposed real-time attendance system based on face recognition using the Viola-Jones algorithm. The evaluation was conducted to measure the system's ability to detect and recognize faces under various conditions, including differences in lighting intensity, face distance, face position, and the use of facial attributes such as glasses, masks, and hats. The results obtained from each testing scenario were analyzed to determine the effectiveness and performance of the developed system.

3.1. System Implementation

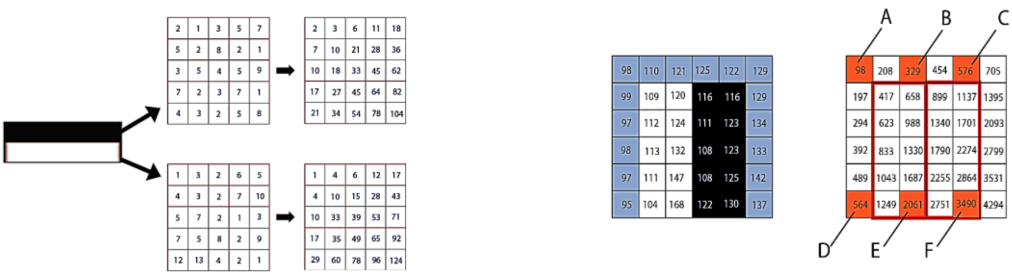
The implementation of the Viola-Jones method and the Haar Cascade Classifier algorithm in this study began after the webcam was successfully initialized. The input image obtained was then automatically converted to a grayscale image (Figure 7a). This step aims to speed up the image processing process, as each pixel has only one intensity value, simplifying and streamlining computation.



(a) (b)

Figure 7. (a) Grayscale Image, and (b) Haar Features Extraction

After the image is converted to grayscale, the next step is to use rectangle features to extract features known as Haar features, Figure 7b, which are used in face detection. Haar features are rectangular and consist of two areas: a light area and a dark area. This feature works by calculating the difference in pixel intensity values between the two areas to identify facial patterns. In the light and dark areas in Haar Features, there are pixel values calculated cumulatively from the left and top of the image using integral image[21],[22], figure 8a-b and formula 1. The feature value is obtained by subtracting the number of pixels in the dark area from the number of pixels in the bright area.



(a) (b)

Figure 8. (a) Integral Image, and (b) Integral Image Difference Value

$$\begin{aligned} VA &= \sum(pixel\ intensities\ in\ white) - \sum(pixel\ intensities\ in\ black) \\ &= (II_E - II_B + II_A - II_D) - (II_F - II_C + II_B - II_A) \\ &= (2061 - 329 + 98 - 564) - (3490 - 576 + 329 - 2061) \\ &= 64 \end{aligned} \tag{1}$$

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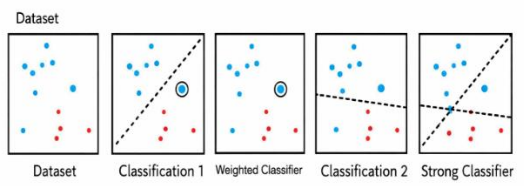
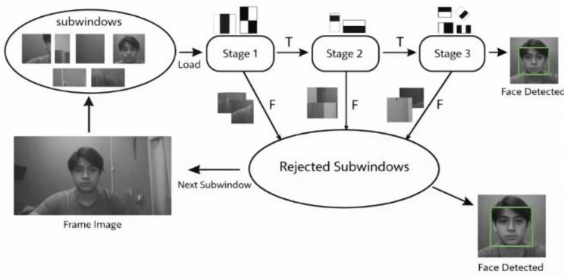
The next step uses the Adaptive Boosting (AdaBoost) method to combine several weak classifiers into a strong classifier, Figure 9a. This process is carried out iteratively until a more accurate classification model is obtained. At each iteration, misclassified samples are given a higher weight, allowing the subsequent classification process to focus more on difficult-to-recognize data. The final stage of the detection process uses the Haar Cascade Classifier, Figure 9b. This method is capable of detecting faces quickly because it gradually filters and eliminates areas unlikely to contain objects. Only areas potentially containing faces are processed further, thus increasing detection efficiency and speed.



(a)



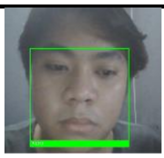
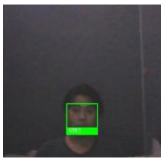
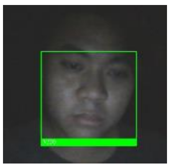
(b)

Figure 9. (a) Classification with AdaBoost, and (b) Haar Cascade Classifier Detection Process

3.2. System Testing

The developed system was tested at varying distances and lighting intensities to determine whether faces could still be detected. The test results are presented in Table 1.

Tabel 1. *First System Test*

Figure	Description	Distance (cm)	Light Intensity (%)	Results
	Perpendicular	25	100	Face Detected Successfully
⋮	⋮	⋮	⋮	⋮
	Perpendicular	100	100	Face Detected Successfully
	Perpendicular	25	50	Face Detected Successfully
⋮	⋮	⋮	⋮	⋮
	Perpendicular	100	50	Face Detected Successfully
	Perpendicular	25	5	Face Detected Successfully
⋮	⋮	⋮	⋮	⋮

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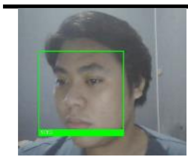
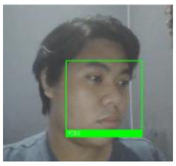
	Perpendicular	100	5	Face not detected

Testing was conducted at distances of 25 cm, 35 cm, 50 cm, 75 cm, and 100 cm with variations in light intensity of 100%, 50%, and 5%. Based on Table 1, the results show that faces can be detected well in almost all conditions, except at a distance of 100 cm with a light intensity of 5%, where the face cannot be detected optimally. This is caused by low lighting so that the facial image becomes dark and difficult to recognize by the system. From these tests, it can be concluded that the system is able to detect faces well if supported by sufficient light intensity and the image capture distance is not too far from the camera.

Tabel 2. *Second System Test*

Figure	Description	Distance (cm)	Light Intensity (%)	Results
	Leaned Left	25	100	Face Detected Successfully
⋮	⋮	⋮	⋮	⋮
	Leaned Left	100	100	Face Detected Successfully
	Leaned Right	25	100	Face Detected Successfully
⋮	⋮	⋮	⋮	⋮
	Leaned Right	100	100	Face Detected Successfully
	Turned Right	25	100	Face not detected
⋮	⋮	⋮	⋮	⋮
	Turned left	25	100	Face Detected Successfully

In the second test in Table 2, various facial positions were performed: tilted to the left, tilted to the right, turned left, and turned right. The test results showed that in the left and right tilted positions, the face could still be detected well at distances of 25 cm, 35 cm, 50 cm, 75 cm, and up to 100 cm. When turned left, the face could also be detected at a distance of 25 cm. However, when turned right, the face could not be detected at a distance of 25 cm. From these results, it can be concluded that the system is still capable of detecting faces well in both tilted and turned left positions. Meanwhile, when turned right, the face is not detected because only part of the face is visible,

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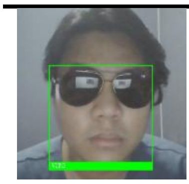
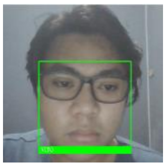
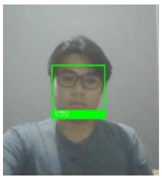
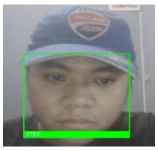
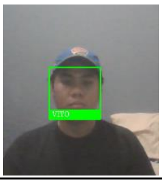
thus facial features cannot be recognized optimally. Conversely, when turned left, the face can still be detected because some important features, such as the eyes, are still visible.

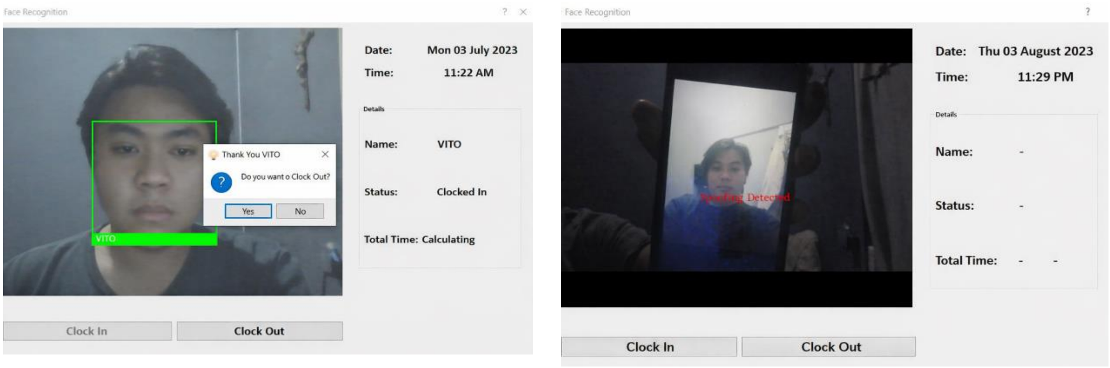
Tabel 3. *Second System Test*

Figure	Description	Distance (cm)	Light Intensity (%)	Results
	Wearing sunglasses	25	100	Face Detected Successfully
⋮	⋮	⋮	⋮	⋮
	Wearing sunglasses	100	100	Face Detected Successfully
	Wearing a mask	25	100	Face not detected
⋮	⋮	⋮	⋮	⋮
	Wearing a mask	100	100	Face Detected Successfully
	Wearing transparent glasses	25	100	Face Detected Successfully
⋮	⋮	⋮	⋮	⋮
	Wearing transparent glasses	75	100	Face Detected Successfully
	Wearing a hat	25	100	Face Detected Successfully
⋮	⋮	⋮	⋮	⋮
	Wearing a hat	100	100	Face Detected Successfully

The third test, shown in Table 3, was conducted using several attributes: sunglasses, white glasses, a hat, and a mask. The test results showed that the use of sunglasses did not affect face detection, with faces still being detected well at distances of 25 cm to 100 cm. When wearing a mask, faces were not detected well at distances of 25 cm and 35 cm, but were detectable at distances of 50 cm to 100 cm. Meanwhile, the use of white glasses showed good face detection at distances of 25 cm to 75 cm. Testing with a hat also showed good results, with faces still being detected at distances of 25 cm to 100 cm. From these results, it can be concluded that the system is still capable of detecting faces even with certain attributes, but the use of a mask can affect detection performance at close range.

3.3. Attendance System Testing

The attendance system was tested to ensure that the system could detect and recognize faces, and record attendance automatically and prevent spoofing, Figure 10a-b. The test results showed that the system performed well under adequate lighting conditions and with appropriate facial positioning. Attendance was successful when faces were registered in the database; unregistered faces were rejected by the system. Overall, this facial recognition-based attendance system improved efficiency and minimized fraud compared to conventional methods.



(a) (b)

Figure 10. (a) Home Attendance Interface, and (b) Anti-Spoofing Feature

If attendance is recorded using images, the attendance process cannot be completed because the system is equipped with an anti-spoofing feature that prevents fraudulent attempts, such as asking for attendance by someone else, Figure 10b. Attendance can only be recorded using faces in real time. Furthermore, attendance data is stored in a CSV file that records attendance information for arrival and departure, including name, time of arrival, and time of departure, Figure 11.

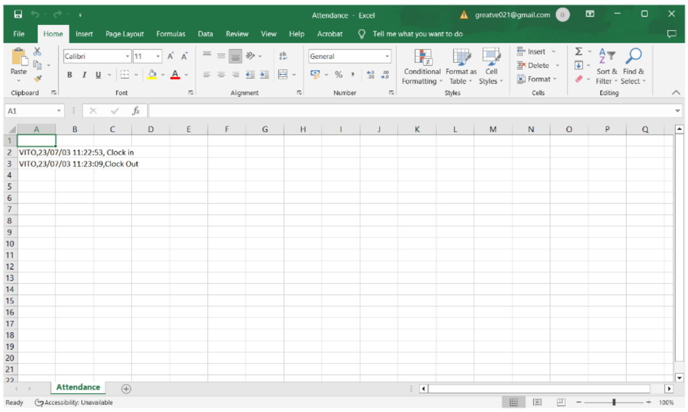


Figure 11. Attendance Data

4. DISCUSSIONS

Based on the test results, the face recognition-based attendance system using the Viola-Jones and Haar Cascade Classifier methods demonstrated quite good performance in real-time face detection. The system performed optimally under adequate lighting conditions and with relatively frontal facial positions. However, system performance decreased in low-light conditions, at excessive distances, and in non-ideal facial positions

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such as extreme head tilts or partial obscuration by attributes. These findings align with previous research, which found that the Viola-Jones method has advantages in detection speed, but is sensitive to variations in lighting and facial angles, see Table 4. Furthermore, the use of Haar Cascade in combination with AdaBoost has been shown to increase detection accuracy to over 99% under certain conditions. Other research has also shown that the Viola-Jones method has an accuracy rate of around 90% under ideal conditions, but can degrade in noisy or low-light environments. This aligns with the test results in this study, where detection failed in low light intensity and long distances. Thus, it can be concluded that the Viola-Jones method is still relevant for face-based attendance systems because it has high speed and simple implementation, but it needs to be combined with other methods or preprocessing techniques to improve accuracy in complex environmental conditions.

Table 4. *Comparison with Previous Studies*

Author & Year	Method	Dataset/Condition	Result	Strength	Limitation
Nidom (2025)[23]	Haar Cascade + AdaBoost	Attribute variations (hat, accessories, etc.)	99.2% accuracy	High accuracy and fast detection	Limited under certain conditions
Sandiva et al. (2024)[24]	Viola-Jones + Median Filter	Face image dataset	±90% accuracy	Stable under normal conditions	Sensitive to noise
Suradi et al. (2023)[25]	Haar Cascade vs Dlib	Real-time detection	Haar Cascade faster	Fast real-time performance	Lower accuracy than Dlib
Bahit et al. (2023)[26]	Haar Cascade	Variations in angle and lighting	Stable detection	Flexible in different conditions	Affected by lighting conditions
This Research	Viola-Jones + Haar Cascade	Variations in distance, lighting, and attributes	Optimal detection under normal conditions	Real-time and lightweight implementation	Sensitive to low lighting and extreme face angles

5. CONCLUSION

This research successfully developed a face recognition-based attendance system using the Viola-Jones method and the Haar Cascade Classifier, capable of operating in real time. Test results showed that the system could effectively detect and recognize faces under adequate lighting conditions, within a reasonable distance, and with a relatively frontal face position. Furthermore, the system is equipped with a simple anti-spoofing feature that prevents the use of images for fraudulent purposes. The scientific contribution of this research lies in the implementation of the Viola-Jones method in an attendance system that is efficient, computationally lightweight, and easily implemented on devices with limited specifications. However, this research has several limitations. The system is still sensitive to low lighting conditions, extreme facial angles, and the use of certain attributes, such as masks, which can degrade detection performance. Furthermore, the method used does not utilize deep learning approaches, which generally have higher accuracy rates in complex conditions. For future research, it is recommended to integrate deep learning methods such as Convolutional Neural Networks (CNNs) to improve the system's accuracy and robustness. Development can also be done by adding more sophisticated liveness detection features, improving dataset quality, and testing in more diverse environments so that the system can be used more widely and reliably.

AUTHOR CONTRIBUTIONS

Vincentius VY: Conceptualization, Data Curation, Methodology, Validation, Writing – Original Draft Preparation;
M. Rifqy Awwaluddin: Project Administration, Supervision, Writing – Review & Editing;

CONFLICT OF INTEREST

The authors declares that there is no conflict of interest between the authors or with research object in this paper.

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