Face recognition using haar cascade classifier and FaceNet (A case study: Student attendance system)

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ABSTRACT

Face recognition is increasingly widely utilised, and there are numerous face recognition systems. Face recognition is typically utilised for attendance on e-learning platforms in the field of education. The haar cascade classifier is one method for face identification; it is used to identify facial areas. Faces are classified using an alternative model, FaceNet. In this research, we purposefully designed an e-learning platform that authenticates students based on face recognition. Based on the findings of this investigation, the system can accurately recognise faces. Ten students were evaluated based on their participation in two attendance trials. Successful presence has an achievement success value of 19, and 1 failed out of a total of 20 attempts. Several variables, such as illumination, and the use of marks on hats, that could have influenced attendance caused the experiment to fail.

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1. INTRODUCTION

An institution must adjust to technological changes in the advanced digital era. A digital switch might take the place of the old manual one thanks to technology. The institution urges all entities to employ digital recording of college student presence as well [1]. Humans have some distinctive characteristics, such as fingerprints, DNA, retina, and faces. As far as security is concerned, this technology serves a bigger good. People have demonstrated a high level of security awareness, making it possible to maintain security without substantially violating their privacy [2]. Biometrics, which include fingerprints, facial features, retina, iris, voice, gait, and palm prints, are statistical data assessments of everyone’s distinctive behavioural and physical attributes and are mostly used for security [3].

Several attendance management systems have been established in recent years to address issues with traditional techniques [4]. Faces are frequently utilised in research to identify people since they are natural and don't need to make direct contact with the sensors [5]. Among the technological advancements that support human labour are face-recognition based presence information systems. The most effective method for identifying persons is face recognition. One area of computer science called "face recognition" uses pattern-based facial contour analysis to recognise or identify individuals [6]. Face recognition technology, in contrast to other biometric and non-biometric methods of attendance, has its own special benefits [7].

Prior to putting the aligned faces into a convolutional neural network to extract identity-preserving features, the traditional deep face recognition system usually aligns faces using basic affine transformations [8]. Each student has a unique facial identity that cannot be impersonated by further proxies. The contributions made by these works are as follows: Two portable devices based on embedded systems for attendance in schools are (1) the best face selection approach using face quality assessment and (2) robust face representation using a deep convolutional network [9].

In this study, Haar Cascade was utilised for face detection because of its robustness, and Local Binary Pattern Histogram technique was employed for face identification. Chinimilli *et al.* [10] suggested a Face identification-based Attendance System employing these two algorithms. According to the study, students' face recognition rates are 77% true positives and 28% false positives. This method can identify kids even if they have facial hair or are wearing glasses. Both with and without using a cutoff value, face recognition of unknown people is close to 60%. With and without using the criterion, it has a false-positive rate of 14 and 30%, respectively.

A comparative analysis of human face recognition by traditional methods and deep learning in a real-time environment was proposed by Jayaswal and Dixit [11]. In this study, we compare two facial recognition models using a real-time dataset: the first is the conventional method, and the second is the deep learning method. The FaceNet model, a deep learning technique, is used to extract the best features from photos and classify each face based on the extracted characteristics. In this testing phase, we have a 96% accuracy rate on our database, which is better than the prior training and testing methods, which took about 92 and 5 seconds, respectively.

Aashish and Vijayalakshmi [12] A comparison of the Viola-Jones and Kanade-Lucas-Tomasi face detection algorithms was proposed by William. In this study, a system that acts as a surveillance camera was used to capture an image of the object while it was moving. Kanade-Lucas-Tomasi only recognised 45% of the complete outcome, whereas Haar Cascade detected 87% of it. It was found that, in addition to the faces that the Kanade-Lucas-Tomasi algorithm could recognise in other photographs, Haar Cascade was able to find faces that the Kanade-Lucas-Tomasi method was unable to in five images.

Technology was discovered to be used in a classroom to track attendance, according to Syed Mansoora *et al.* [13]. Face recognition accuracy for a class of 28 students is roughly 95% if the photo capture parameters (such as light, face distance, and expression) are constant. There are several places, nevertheless, that could use future improvement. Several things to consider regarding the current system It is composed of three phyton programmers, and command-line inputs are necessary for it to operate.

There are numerous face-recognition algorithms that have been mentioned previously [5]–[13], yet there is still a performance barrier when it comes to utilisation. In this instance, student face recognition requires light performance. Additionally, a single school enrols a lot of kids. Based on the problems, we combined two different algorithms in this study: FaceNet, which produced the value of the face matrix required to determine the identity of the face, and the Haar Cascade Classifier, which was used to categorise student facial areas for attendance. In this study, it is hoped that by combining the two approaches, student face detection will be more efficient and accurate.

2. METHOD

This study builds a face recognition system using web-based face identification technologies together with the Haar Cascade Classifier technique, which is utilised to distinguish between different face areas. Utilise face training with the FaceNet model to create the proper face matrix using the faces in the database to get information on student attendance. Figure 1 are describing the research stages, more following description of the phases conducted research.

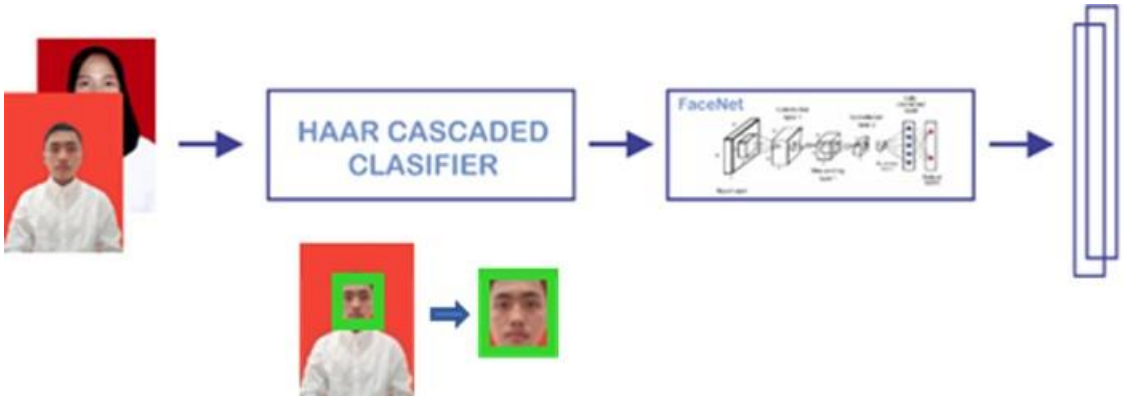


Figure 1. Research stages

2.1. Dataset collection

To conduct this research, the first step is to collect data, which comprises of student and face data that is currently available through the academic system. In this study, 10 photographs of each student's face were taken to represent all the participants in the study. The information will then be saved to a database.

2.2. Data processing

2.2.1. Preprocessing

In this study, the preprocessing stage involves several methods to ensure optimal data quality before the main analysis. First, the Haar Cascade Classifier is used to detect facial areas in images captured by the camera, allowing for the isolation of faces from the background. Next, Convolutional Neural Networks (CNN) are applied to extract important features from the detected faces, enhancing the accuracy in recognizing facial patterns and structures. Finally, FaceNet is employed for face classification and recognition, ensuring that each detected face can be accurately identified based on the previously extracted features. Several process methodologies are employed in this research:

A. Haar cascade classifier

A classifier is trained using many both positive and negative images in the Haar Cascade Classifier machine learning technique. Michael Jones and Paul Viola proposed the algorithms [1]. The image is divided using the Haar Cascade Classifier based on the red, green, and blue values, which range from 0 to 255. The system can differentiate the features of the image thanks to these three fundamental hues. The first array matrix that is created is red, the second array matrix that is created is green, the third array matrix that is created is blue, and so on for the other colours in the background [14].

The system determines the characteristics of objects using these images, which are created from the combination of these arrays and pixels. B * A3 is used to compute the image's size. Different RGB value intensities are provided by each element of the matrix. It becomes easier for the system to detect utilising a single channel for black-and-white images [1], [5]. To find faces and classify specific areas of an image as faces, Haar use a sliding window method that spans a 24 x 24 area over the entire image.

- Haar feature

In a detection window, Haar-like features consider nearby rectangular sections, sum their pixel intensities, and then compute the difference between these sums. Sub-sections of an image are categorised using this distinction [7]. The next step is to use a mixture of boxes to find a better visual object. Each Haar-like feature will be made up of a combination of black and white squares, as seen in Figure 2.

The Haar-like feature comprises three different kinds of boxes:

a) Indicates that the difference between the sums of the pixels within two rectangular portions that have the same size, shape, and placement determines the values of two rectangular features.
b) By reducing the sums of two outside rectangles from the sum of a center rectangle, the values of three rectangle characteristics are displayed.
c) The disparities between diagonal pairs of rectangles are used to calculate the four rectangle features [9].

The average number of dark pixels minus the average number of light pixels is used to calculate the values of the Haar-like characteristic. The number of grey-level pixel values in the black box and the white box represents the value of the Haar-like feature. If the difference is greater than the cutoff point, the characteristic can be assumed to exist. On (1), you can see the Haar Formula [15].

$$f(x) = \sum \quad BlackRectangle - \sum \quad WhiteRectangle \tag{1}$$

Information:
$f(x)$ = Total feature value
$\sum \quad BlackRectangle$ = Value of features in dark areas
$\sum \quad WhiteRectangle$ = Value of features in bright areas

Using the (1), the box on the Haar-like feature may be computed as "Integral Image".

- Integral images

Integral images are a method for quickly calculating feature values by re-representing each pixel's value as a new image. The use of an integral image makes it simple to spot the existence of Haar characteristics at different scales. The sum of all pixels from top to down makes up each pixel's integral value [16].

Figure 3 is a calculation of integral image and Haar-like features. When all the pixels in the rectangle region from the top left to the location (x,y) have been integrated, the value at the pixel position (x,y) in Figure 3(a), also known as the darkened area, reflects the sum of all the pixels in the region. Ii(x,y) is the value of the integral at point (x,y), according to (2):

$$ii(x, y) = \sum \quad x' \leq y' \leq \ y^i \text{ (x',y')} \tag{2}$$

where:
$ii(x, y)$ is a complete picture at coordinates x,y
$i(x', y')$ is the value of each pixel in the original picture

By calculating the integral image value at four different locations, it is possible to quickly calculate the value of a feature in Figure 3(b). The number of pixels in area D can be calculated using techniques 4+1-(2+3) if the integral value of picture point 1 is A and the integral values of picture points 2, 3, and 4 are A+B+C+D.

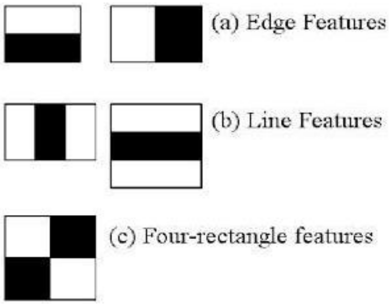
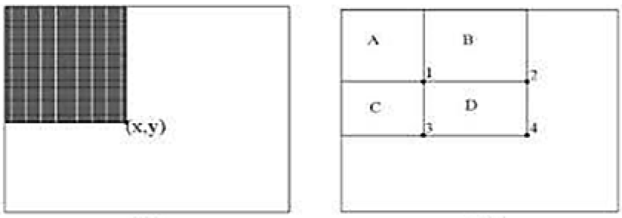


Figure 2. Haar-like feature



(a) (b)

Figure 3. Integrated all pixel in the rectangle region (a) darkened area and (b) integral image at four locations

- Frontalface classifier

The frontal face problem has been greatly improved by Viola and Jones' work, but multi-view face detection is still challenging because faces' appearances change significantly depending on the stance, lighting, and emotion [17]. The Viola Jones detector works effectively for front faces but is useless for non-frontal faces because of the limitations of the haar characteristics. For non-frontal face detection with significant position fluctuations, the cascade classifier of Viola and Jones was utilised [10]. It is necessary to create a frontal face classifier with extremely high precision. Positive sets consist of frontal face classifiers, and negative sets consist of non-frontal faces. A neural network and a cylinder head model are two possible methods for building a frontal face classifier [11].

Several Haar features in an image are processed by the OpenCV library while reading Haar features, in particular, haarcascade_frontalface_alt. In this study, facial regions in certain pictures were located using the Haar Cascade method and then given a bounding box designation. The image will be cropped depending on the available bounding box once the facial region has been located.

B. Convolutional neural network (CNN)

One of the artificial neural architectures used in deep learning for processing data in array format is the convolutional neural network (CNN). CNN uses convolution techniques on one or more of its layers, taking inspiration from the organic neural network [12]. One of the most popular Deep Learning image categorization methods is CNN. It is especially well suited for mask detection from photos of faces because it can categorise items from 2-dimensional images. Given that CNN is capable of learning regional patterns from a tiny window or area within an image, it will recognise the mask and eventually apply to moving objects using OpenCV [18]. The classification process and feature extraction are the two phases that make up the CNN framework. The extraction operation is done on the convolution and pooling layers, which will produce feature maps. The output of the first convolution layer serves as the input for the succeeding convolution since CNN is hierarchical [19].

The output of the feature extraction process will be converted into a single dimension before being sent to the classifier, which may be a fully connected layer, as shown in Figure 4, during the classification phase. The fundamental building block of CNN is the convolutional layer. Understanding that the layer parameters in CNN technology are composed of trainable filters known as neurons is essential. These filters go through the entire input volume despite having a limited receptive field. Each filter in the forward-pass method traverses the input volume's width and height while computing the dot product between the filter entries and the input [20].

The layer created by downsampling the input image is known as the pooling layer or the feature mapping layer. The network's compute layers are made up of several feature maps, each of which is mapped to a plane and given equal weights by all the neurons in that plane. To achieve displacement invariance, the feature mapping structure employs a tiny sigmoid function that has an impact on the convolutional network's activation function [21].

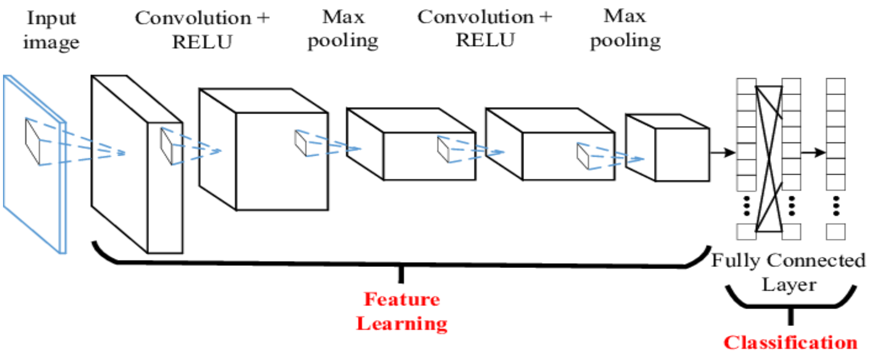


Figure 4. Convert feature extraction into single dimension

C. FaceNet Architecture

FaceNet is a facial recognition system created by Google researchers. To recognize features in a facial image, a deep neural network known as FaceNet is employed. FaceNet takes a face picture as input and outputs an embedding, which is a vector of 128 values that symbolizes the most important characteristics of a face. The FaceNet first transforms the face image into 128-dimensional vectors, which are then placed in Euclidean space. The FaceNet model that is created in this way is trained for triplet loss in order to capture the similarities and differences in the input image dataset. Using the 128-dimensional embeddings of the model, faces can be clustered considerably more successfully and precisely. FaceNet embeddings as feature vectors may be used to implement features like face recognition and verification after the vector space has been constructed [22].

A batch input layer, a deep convolutional neural network, followed by L2 normalisation, which provides the face embedding, make up the FaceNet network architecture. Triplet loss then occurs because of this process [23]. The network is trained in such a way that squared L2 distances in the embedding space directly correlate to face similarity; faces belonging to the same person have small distances, whereas faces belonging to different persons have high distances [24]. A triplet loss function or set of three images made up of an anchor image, a positive image that is the exact same as the anchor image, and a negative image that is distinct from the anchor image, is used in FaceNet mode [25].

If a triplet set contains an anchor, positive (same class), and negative (different class) images, it is said to be legitimate. The embedding anchor distance, which has a positive value less than the negative anchor distance, is the triplet's objective function [26]. In this work, feature learning is done using FaceNet. Each student's face prints, or face matrix values are collected using FaceNet, which is also utilised to recognise the face identity of students who take attendance through facial training.

2.3. System design and implementation

The design and implementation of the system involved the use of hardware and software. The design that will be implemented is analogous to developing a table-based database. In addition to displaying the user interface, it is required to do so during system design.

2.4. Testing

The testing dataset is comprised of a student photo dataset that has been placed in a database and then executed in software using the phyton programme. The input test is conducted with the camera shown in the image box. If the data is present in the database, it is possible to record student attendance.

3. RESULTS AND DISCUSSION

This chapter examines the implementation of the interface procedure. The programming language used is phyton with the OpenCV library added. The Haar Cascade Classifier algorithm serves as a face area detector, whereas FaceNet compares the input image to the photo in the database. Figure 5 illustrates the system flow for detecting faces. The Haar Cascaded Classifier identifies the facial area visible on the camera, and then FaceNet classifies to recognize the face for presence.

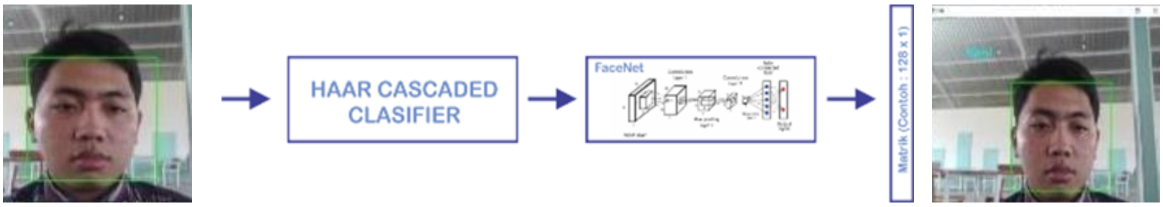


Figure 5. Face detection step

The performance results of face detection will be carried over to the subsequent procedure, which is the face recognition of students to record their attendance during lectures. And the failure in face detection is the result of an insufficient initial analysis. As a result, in this research, we selected the Haar Cascade Classifier as a method for analysing face areas because, in our opinion, it can detect face areas accurately, and we selected FaceNet as a face training method since it can also recognise faces accurately.

A. Dataset

The dataset used in this research is in the form of face images obtained from collecting student photos. In this research, what was the process of selecting a dataset that had quite a variety of face variations and met the minimum number of photos so that 10 students could be obtained. Each student has 10 photos. So, the total number of photos available is 100 out of 10 students. Figure 6 displays numerous photos of students' faces stored in the database.

id ▲ 1	nama_id	foto1	foto2	foto3	foto4	foto5
1	1	dataset/hilmi_w4YqcEj.jpg	dataset/hilmi_8SDv30i_n0RFqm8.jpg	dataset/hilmi_ai7AyUN_ZyO2nbh.jpg	dataset/hilmi_BBUzlet_XgGJFMc.jpg	dataset/hilmi_eurkZFO_QZM1d8L.jpg
2	3	dataset/galuh_xigixdo.jpg	dataset/galuh_2hJkQI0_a0DuN9f.jpg	dataset/galuh_5goptpv_2MRhOel.jpg	dataset/galuh_92H0lnA_SNnEual.jpg	dataset/galuh_Bh0AhqY_adzVbWQ.jpg
3	2	dataset/tanti_x7bh2X1.jpg	dataset/tanti_9n2nGD2_5XnbeNc.jpg	dataset/tanti_AYpWjjM_LrLnUDJ.jpg	dataset/tanti_BydvkjR_2z8irQo.jpg	dataset/tanti_fjEuEhP_3TWBIZF.jpg
4	4	dataset/ilham_d2oB1IA.jpg	dataset/ilham_0V6Mkwj_V0oz1jD.jpg	dataset/ilham_7xSiHCx_bUdkZBJ.jpg	dataset/ilham_ht9lvol_lY1iPYL.jpg	dataset/ilham_DzwYSzs_BDHeSmX.jpg

foto6	foto7	foto8	foto9	foto10
dataset/hilmi_lmeaHZd_RC9GTH9.jpg	dataset/hilmi_WvaN9Jf_uCvyPuF.jpg	dataset/hilmi_pzoPZPx_DuT6lri.jpg	dataset/hilmi_P60ss2x_Qnbg8H5.jpg	dataset/hilmi_cyPhlZb_9ngRUOe.jpg
dataset/galuh_BJehLJB_eP6Jtqy.jpg	dataset/galuh_h1SaPxs_AyCZd7s.jpg	dataset/galuh_oXS1KiD_aejMP2W.jpg	dataset/galuh_uuh8MGQ_bZrTPtl.jpg	dataset/galuh_ZqRu5jP_uVw3l0L.jpg
dataset/tanti_GXGDyTl_gMANRrs.jpg	dataset/tanti_LGy4baM_ilqq4Ev.jpg	dataset/tanti_pgXrV6y_B7HZ11H.jpg	dataset/tanti_R66eZlh_JeyJQTD.jpg	dataset/tanti_Y6xQOIl_DuO3jtT.jpg
dataset/ilham_EqB3bPj_hXffwaq.jpg	dataset/ilham_LSlhYcb_XCEGcB5.jpg	dataset/ilham_phDfv5T_O8X2ik6.jpg	dataset/ilham_zEn5QJW_68tOIGS.jpg	dataset/ilham_bBJZ6sK_UGEferL.jpg

Figure 6. Student’s photo table

B. System planning

Student attendance application utilising face recognition in real time based on a website employing the haar cascade classifier and FaceNet algorithm. Using a WebCam on a personal computer, the system detects faces in front of the classroom. After a face-shaped object has been detected with a green face-shaped rectangle, face training will be conducted with FaceNet in order to recognise the face that is there. If the face is already in the database, it will be identified. The student data will be saved on the server as proof of attendance at the lecture when the student’s face input data has been identified as the input source.

C. System implementation

The image shows how the system works Figure 7, which is the flow of the attendance system. Before students take attendance, the administrator must first login to the website and then select a timetable based on the room session’s schedule. The student then takes attendance according to the hours stated on the schedule, and once attendance has been taken, the results are recorded on the attendance page.

The system operates as shown in Figure 8 by identifying faces in front of the classroom using a PC's webcam. Once a face is detected, it is marked with a green rectangular box for face training with FaceNet to identify the face. Recognition of faces occurs when the face is already in the database. Following the recognition of the student's facial data, it is then stored on the server as evidence of lecture attendance.

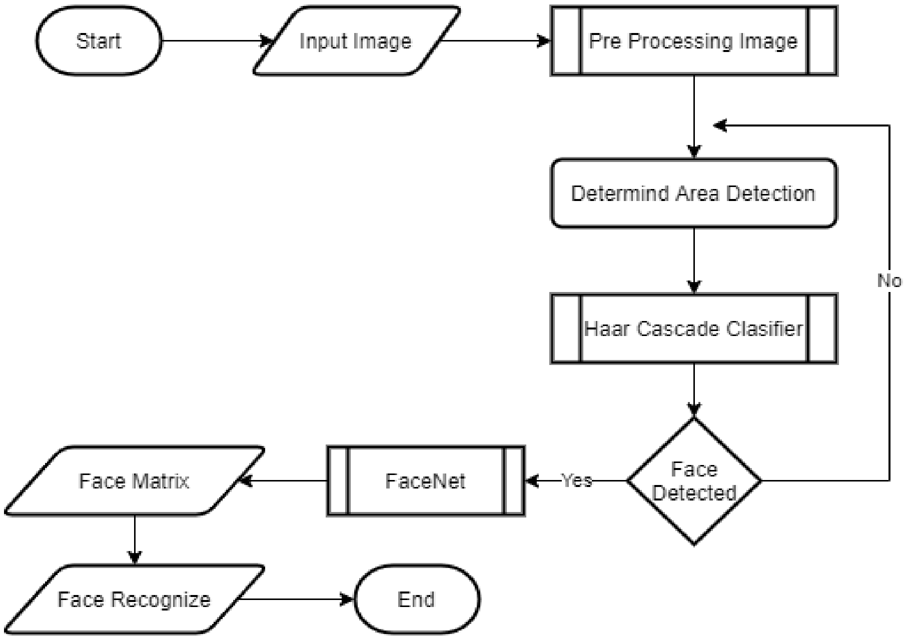


Figure 7. Flowchart diagram

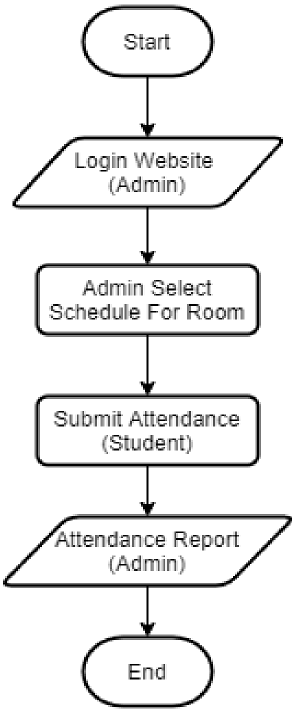


Figure 8. System flow

1) Dashboard page

Figure 9 is a dashboard page that serves as the homepage of the administration site. There is information regarding registered user data, student data for students who have taken attendance, and student data for students who are not absent. This page also provides information like the room, course, time, class, and semester.

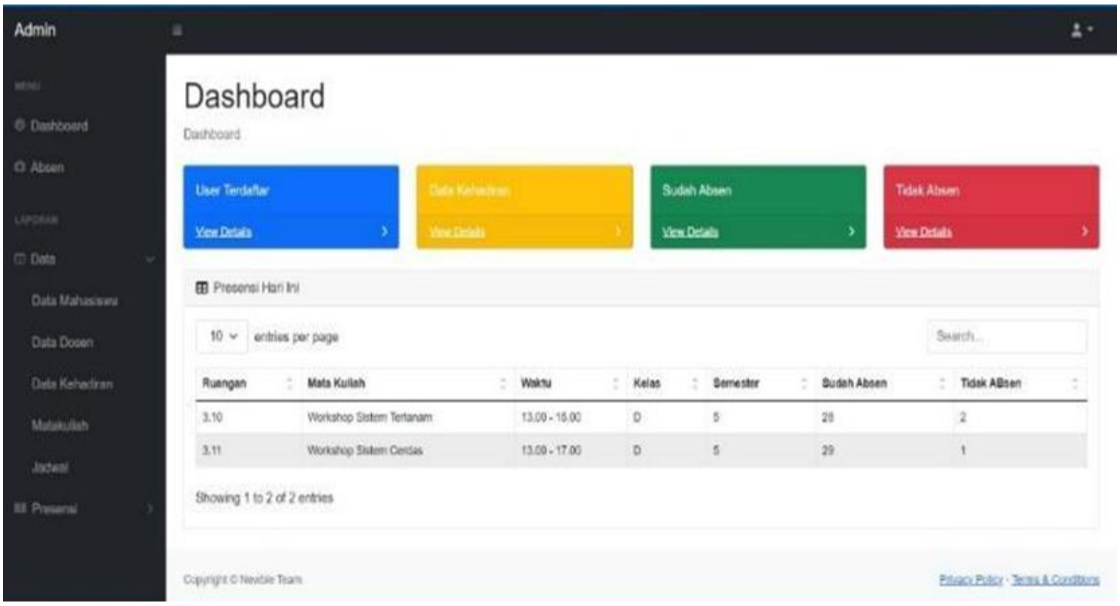


Figure 9. Application dashboard

2) Presence page

Figure 10 is the presence page, on this page there is NIM information, a photo, a name, course, date, time, status, and an action. This is data about students who have attended class. Students mark their presence directly to ensure that the data is stored in the database.

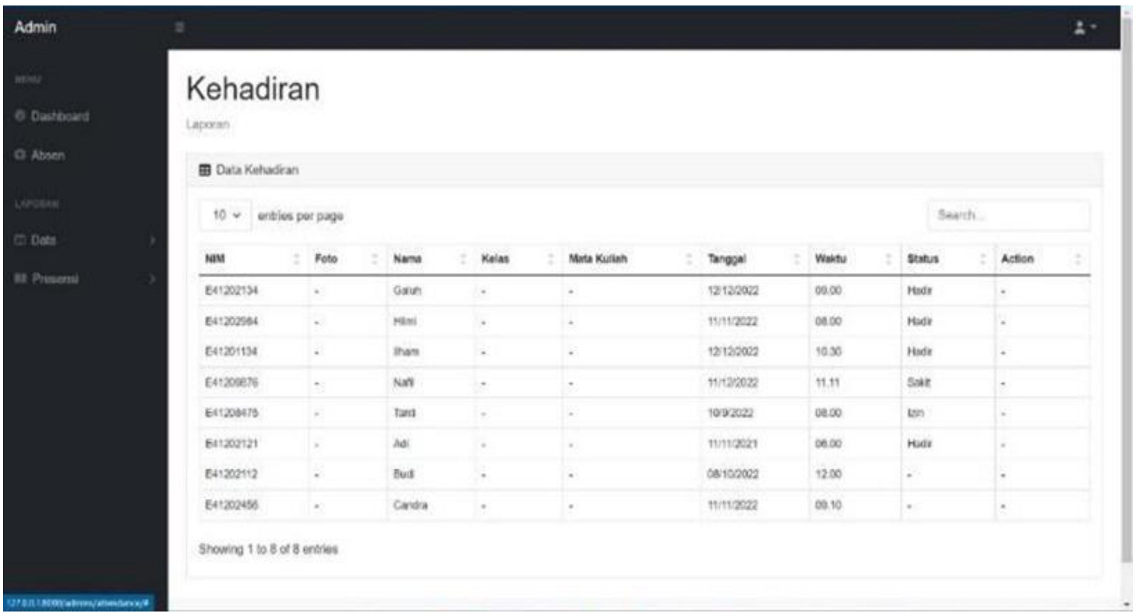


Figure 10. Presence page

3) Student data

On the student page in Figure 11 are the NIM, name, class, semester, telephone number, address, and gender of the student. There are capabilities to add student data, edit student data, delete student data, and export student data reports. All student data can only be accessed, modified, and removed by the admin.

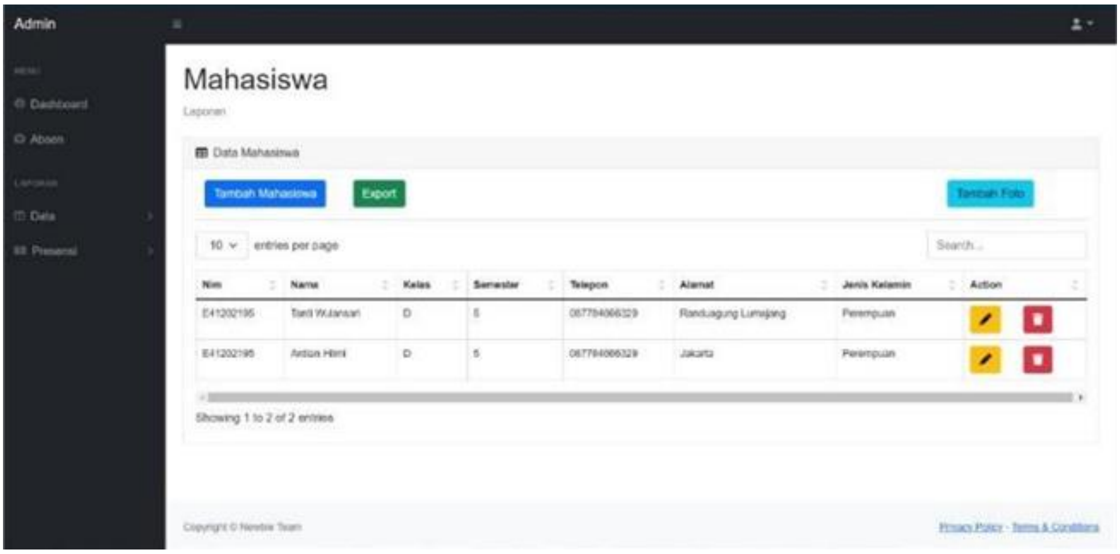


Figure 11. Student data

4) Schedule page

The administrator will utilise the schedule page to determine the presence to be displayed on the PC used for attendance. There are numerous statistics, including day, course, professor, classroom, and course hours. In Figure 12 is the schedule page from the presence website.

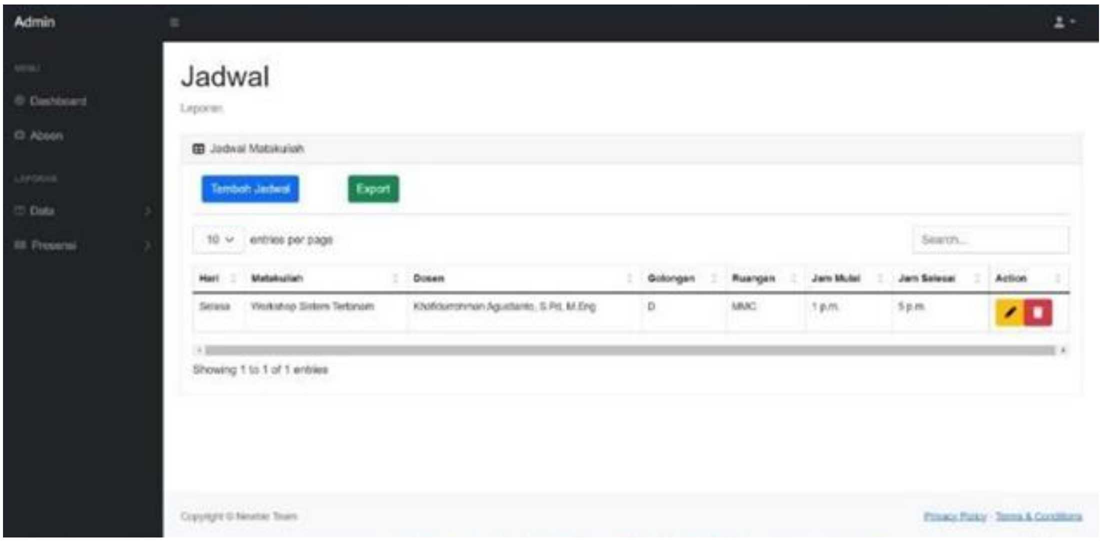


Figure 12. Schedule page

5) Attendance page

This attendance page serves as a page where students record their attendance. The room contains some information regarding the course schedule. Figure 13 shows a camera to detect the faces of attending students. If the data is recognized, the student's presence is confirmed.

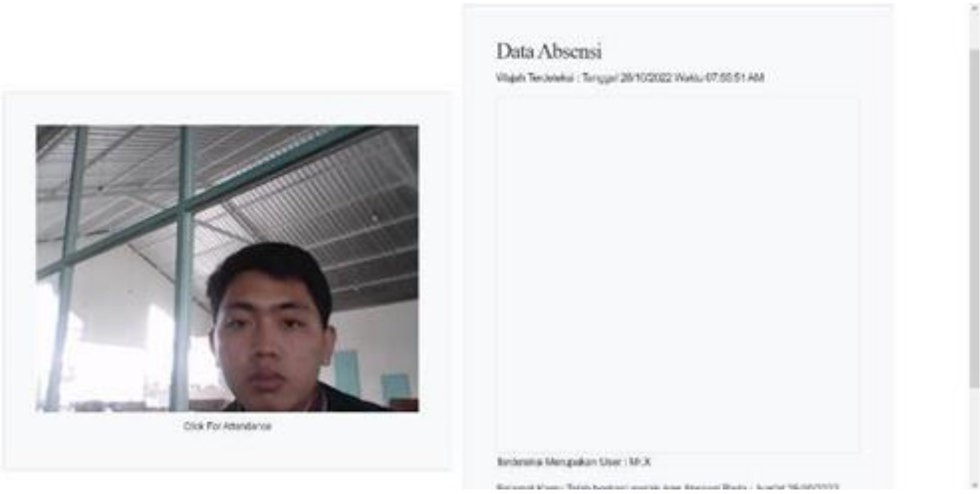


Figure 13. Attendance page

D. System testing

Direct presence experiments on previously created applications are used for testing. Students take attendance one by one, and if the student's face is recognised, the system records the student's existence. Figure 14 is a trial of the face recognition system. If the face is recognized, there is a box with the name of the student present.

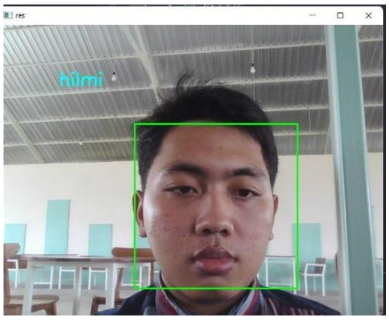


Figure 14. System testing

E. Testing

In this research, testing was conducted by incorporating a dataset. The test results are expressed as a facial recognition accuracy value. The accuracy is determined by the number of models capable of accurately classifying the students faces. After analysing the data from 10 enrolled students in the dataset, the test result based on the correctly identified number is 9 students and an imprecise number of 1 student. Then the (3) can be used to determine the level of precision attained:

$$Accuracy = \frac{Number\ of\ successful\ tests}{Amount\ of\ data} \times 100\% \tag{3}$$

The implementation of the Haar cascade classifier and facenet is capable of producing 90% accuracy. This result is better than that done by Saleem of 82.432%. So the application of Haar Cascade Classifier and FaceNet can increase accuracy by 9.568%.

The accuracy value that was achieved in this research is a promising result. In the case of student face recognition in the student attendance system, the Haar cascade classifier and facenet algorithms are suitable. Because of its promising accuracy and light-use performance. Researchers have also already developed a prototype that uses a web-based application. The prototype has some basic features, such as registration, reports, and a student attendance system. In the main features of student attendance, the Haar cascade classifier and facenet algorithm were successfully implemented with only a few seconds to respond.

4. CONCLUSION

From the research and testing of the system that have been carried out, the following conclusions are obtained: i) The student presence system can be done using face recognition and ii) The level of accuracy in face recognition with the Haar Cascade Classifier and FaceNet methods is 90%. So, it can be concluded that this system can work well and is quite accurate. For further research, we suggest that more datasets be used from each student, and the use of the Haar Cascade and FaceNet methods can be further developed by future researchers in order to obtain better results, such as using a better face detection method than the Haar Cascade method and researching other architectures on deep learning methods.

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