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# Principal Component Analysis and Regional Coordinates on Face Recognition in Mobile-Based Attendance Systems

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**Abstract**

The pattern of attendance in the world of work after the Covid-19 outbreak that hit the world, has apparently brought quite big changes, due to the taboo on gathering and using shared media which is considered a medium for the spread of bacteria/viruses. The way out of this is to use facial recognition and collaborate with location coordinates using a mobile application that can be used on each smartphone to authenticate workers in changing the characteristics of presence data, so that the presence process cannot be represented. The method used for face recognition in this research is Principal Component Analysis (PCA) by linearly transforming eigenvalues and eigenvectors from extraction and reduction of faces captured from the mobile presence application. Based on the trials carried out, the success rate reached 78,667% for testing the functionality and strength of facial recognition.

Keywords: Presence; Face Recognition; Mobile; Principal Component Analysis; Regional Coordinates

## 1. Introduction

Current technological advances have entered a new era, namely the industrial era 4.0. This is the impact of developments in the industrial world which require high speed and mobility. So this has an impact on various devices that are used to facilitate various kinds of activities because essentially this technology itself is used to disseminate information to achieve a goal (Yona Sidratul Munti & Asril Syaifuddin, 2020). One of the devices that are the main points in human activities today is a smartphone device, where everyone who does activities, especially in urban areas will have a dependence on this device.

Before the pandemic hit the world, many authentication models for presence in offices used fingerprints as the main medium. This has become a taboo thing to do during the Covid-19 pandemic. One way to break the chain of spread of the Covid-19 virus is social distancing, with a very simple example being putting your hands in public places or equipment (Triputro & Supardal, 2021). Until now, there are many substitutions for the detection of presence, one of which is the approach model of IP address smartphone users. Based on the use of this IP address, smartphone devices owned by users will carry out the attendance process with a specified coverage area, namely with coverage area by wifi in the office. So that for the implementation of the concession, connectivity with wifi in the office area is needed. This certainly will not be able to replace fingerprint-based authentication patterns, which require each individual in the office to carry out their attendance process. The use of the attendance model with IP address and coverage area has weaknesses, namely that it cannot be authentically identified whether the person who carries out the attendance process is the person concerned, as in the fingerprint model. This is one weakness in the model. The weakness of using a presence system that only uses IP addresses is that someone can entrust the device to another person, so that fraud can occur in carrying out attendance.

Adopting these weaknesses, this research provides a solution, namely a presence authentication model based on face recognition which is a method with a facial recognition process (Arsal et al., 2020) and area coverage using satellite data that captures coordinates from latitude and longitude (Hajar et al., 2021). The problem that will be studied is facial data with recognition patterns based on eigen values and eigen vectors. The scope


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of this research is limited to applications made using one facial recognition method, namely Principal Component Analysis (PCA) and making an Android mobile based application because PCA is considered reliable in terms of extracting dataset structures with various dimensions (Saepurohman & Putro, 2019). Combining multiple types of features, e.g., color, texture, and spatial structure, is useful for finding more informative matches (Guo et al., 2020). This presence model will look at the area where the worker is present, so that facial image data and latitude longitude data will be recorded from the user of this application based on satellite data, so that it will be detected authentically and actualy.

The specific purpose of this study is to assist in the alternative of replacing the attendance authentication model that originally used fingerprints with face recognition, so that authentication of attendance actors remains characterized according to their biometrics. In addition, the purpose of this study helps in optimizing time efficiency by simplifying the mobile attendance model, so that it can be done anywhere, anytime, and under any conditions. The intended urgency is the transformation of the attendance model by prioritizing the mobilization of the use of technology.

The existence of Covid-19 makes it necessary to switch the attendance model from the original use of fingerprints to something safer, namely the use of facial recognition (S. P. Putra et al., 2021). The face is the most memorable part of the body which makes it an important variable in life in the real world (Ramadhani et al., 2018). In general, facial recognition is divided into two types, namely feature-based and image-based, face recognition with image-based one of which is in the Principal Component Analysis (PCA) method (Harto & Rahmani, 2019). PCA is a robust method of use in the features of extraction techniques for facial recognition (Abbas et al., 2017). Beside that, PCA attempts to project the data along an optimal direction by maximizing the ariance matrix of data (Sen & Xia, 2018). The eigenface in PCA is the part tasked with extracting characteristics (Simaremare & Kurniawan, 2016). In facial recognition, there are several influencing factors, including lighting, face position, and face distance to the camera (Susim & Darujati, 2021), unrestrained situations in facial shooting are challenging, given variations in lighting, expressions, and poses are very important (Lin et al., 2021). Facial recognition in computers is included in biometric research, which is the measurement of characteristics in a person for automatic recognition of the identity of that person (Budi et al., 2016). One of its uses is for attendance systems that can be applied using a mobile application base (R. R. C. Putra & Juniawan, 2017). The use of smartphones as a medium for attendance is something that is used to streamline time (Kosasih & Daomara, 2021). Testing on the attendance system was carried out with two scenarios, namely for arrival hours and return hours (Syuhada et al., 2018).

## 2. Method

This research uses primary data sources, which were obtained directly from respondents who were used as research objects and original data and were not subjected to any statistical treatment (Sari & Zefri, 2019). The data used is divided into two sets, the first is training data, which contains 150 facial images. then the second is test data which is used to directly test the use of this method with a capture camera. Method could encounter performance drop inevitably in a fully unconstrained scenario for the intrinsic noise of the images (Zhao & Deng, 2022). Beside that, the data observed in this study is divided into two parts, namely input and output. The input data observed is a color digital image image taken by the camera in a mobile phone which is implemented into a two-dimensional matrix with RGB completeness in a certain order size. Then on the output, the observed data is the matching result of the outgoing image as well as the highest percentage value of the matched image. In its measurement, the measured data is grayscale matrix data formed from the process of changing the RGB image obtained.

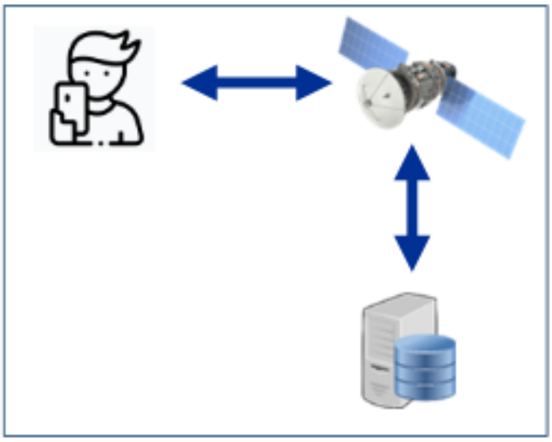

Figure 1. Architectural Design


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In Figure 2, it can be seen that the attendance model carried out utilizes satellite networks. This utilization is intended for communication between applications on smartphones and databases that contain personal user data and of course, a collection of facial images of each user registered in the database. In addition, the use of satellites here also aims to obtain latitude and longitude coordinate values from application users to be able to record and enter into the database to find out the whereabouts of users when carrying out attendance activities. The system design implemented is divided into several stages, namely:

a. Process from analog to digital
In this process, images of analog objects are captured using an application in digital form by a smartphone camera.

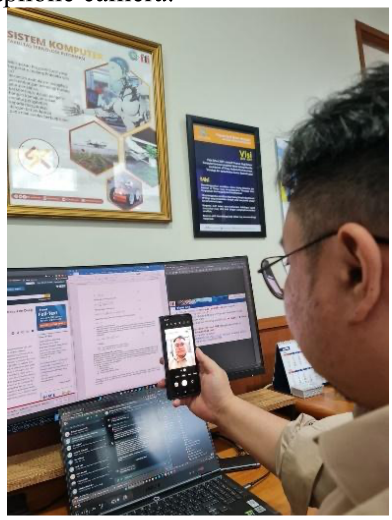

Figure 2. Taking Picture

b. RGB to grayscale
After the image is taken, it will be an image with an RGB pattern. The image needs to be converted into a grayscale form for later processing.


Figure 3. RGB to grayscale

c. Grayscale matrix size adjustment
Furthermore, from the grayscale image obtained, the size of the image obtained will be adjusted to the size of the image on the data that has been collected in the database. The size of this image should be square. In its adjustment, the image matrix obtained is converted into a size of 200x200 pixels.

d. Matrix processing with PCA
Convert a 2-dimensional matrix into a 1-dimensional one, by:
1) Calculate the average value
$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \quad (1)$$
2) Calculate the deviation value from the average
$$(\sigma) = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})^2} \quad (2)$$
3) Calculate matrix covariance
$$cov(x, y) = \frac{1}{\sum a_i^2}\sum_{i=1}^{n} a_i^2 (x_i - \mu_x)(y_i - \mu_y) \quad (3)$$
4) Calculate eigen value, and eigen vector
$$Ax = \lambda x \quad (4)$$

e. Image classification for results
The classification uses the euclidean distance approach to obtain the proximity value between the eigenface value obtained from the input image and the eigenface value of the image in the database. Here is the formula of the euclidean distance used:
$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \quad (5)$$

## 3. Results and Discussion

There are two kinds of architectures formed in this attendance application, first the front end for views that interact with users and the back end as a facial recognition process from data in the database. The front end displays the view inside the mobile phone as a device used for data retrieval of the presence. The data is obtained from the front camera capture on the mobile phone and obtained the results as attached to Figure 4.

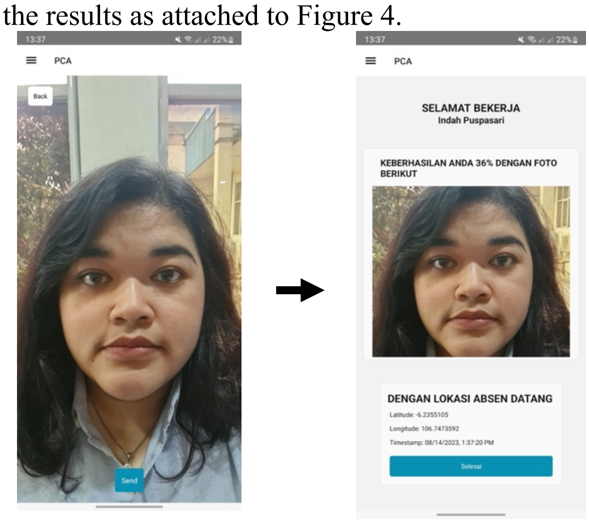

Figure 4. Presence Process


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From the attendance process above, the next step is a trial of the function of the application as a container for conducting attendance. This is based on several experiments, the experiments carried out are as follows:

a. Face Position
Table 1 describes the results of testing respondents' face positions against the app's camera view. In the table, the value of 36% to 41% is the similarity value obtained from using the PCA method based on testing position.

Table 1. Testing on face position

| Position | Success | PCA |
|---|---|---|
| Center | √ | 36% |
| Top Right | √ | 36% |
| Top Left | √ | 41% |
| Bottom Right | √ | 35% |
| Bottom Left | √ | 35% |

b. Smartphone Position
Table 2 is a smartphone-side test when conducting attendance on respondents who are not facing the camera.

Table 2. Pengujian pada posisi smartphone

| Position | Success | PCA |
|---|---|---|
| Right | √ | 37% |
| Left | √ | 39% |
| Top | √ | 33% |
| Bottom | √ | 36% |
| Right diagonal | √ | 32% |
| Left diagonal | √ | 39% |

c. Lighting
The tests attached to Table 3 use exposure levels when preceding. The lighting levels in this study were divided into three, namely bright, normal and dark. In bright the value is 32,000-100,000 lux, in normal the value is 10,000-31,000 lux and in the dark the value is 1-9,000 lux.

Table 3. Testing at lighting levels

| Lighting | Success | PCA |
|---|---|---|
| Bright | √ | 41% |
| Normal | √ | 33% |
| Dark | √ | 30% |

d. Accessories
In the test attached to Table 4, respondents were asked to wear several accessories on the face and head area.

Table 4. Testing with the use of accessories

| Accessories | Success | PCA |
|---|---|---|
| Glasses | √ | 34% |
| Mask | √ | 34% |
| Glasses + Mask | √ | 35% |
| Hair Tie | √ | 34% |

Adopting the tests that have been done, the results are obtained that the functionality can function properly, the success of obtaining the results of the comparison of profile photos and attendance photos also functions well and the average PCA results obtained 36% that is because of the scaling of variables when taking images is very influential, so it is very sensitive to the image taking process when compared with the data in the database, from the tests above, it can be seen in figure 5 overall success of the attendance application.

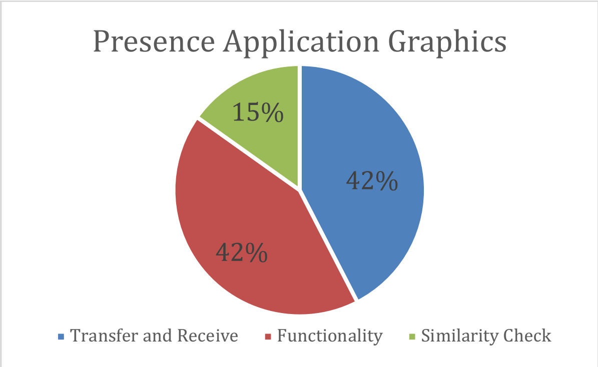


Figure 1. Overall success graph against attendance applications

## 4. Conclusion

Based on tests conducted on facial recognition against datasets in the database are as follows: a) Experiments conducted on functionality get 100% accurate results, according to the function for which it is intended. b) Face recognition with experiments based on face position, smartphone position, lighting, and use of accessories against the camera was 100% successful. c) The average PCA result, where the comparison of profile photos with the resulting attendance testing is 36%. d) The success rate reached 78,667% from testing the functionality, success, and power of facial recognition.

A face tracking mechanism is needed so that when taking a face it can be seen that the face image is detected accurately or not. In addition, it is also necessary to have a success accuracy value, so that it can be used to make significant comparisons.


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