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Application of centroid and geometric mean methods for face recognition

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ABSTRACT

Face recognition is one of the most important areas in artificial intelligence and image processing, with wide applications from attendance system security to human-computer interaction. This study aims to overcome the difficulties in classifying student faces in an academic environment by applying and comparing centroid and geometric mean methods. Student face data was collected and processed through conversion to grayscale, pixel intensity normalization, and statistical analysis using both methods. The results showed that both methods had the same performance with 70% accuracy, 75% precision, 60% recall, and 66.67% F1-score. The application of this method can improve the efficiency and accuracy of attendance management and security in the campus environment, especially for institutions with limited resources.

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1. INTRODUCTION

Face recognition is one of the very important fields in artificial intelligence and image processing (Tian, 2020). This technology has various applications ranging from security, attendance systems, to human-computer interaction (Masud et al., 2020). In academic settings, such as at STMIK YMI Tegal, facial recognition can be used to increase efficiency in managing student attendance and improve campus security. The problem faced is the difficulty in classifying student faces quickly and accurately in a dynamic campus environment (Ali et al., 2021). Conventional methods, such as the use of identity cards or manual attendance lists, are often inefficient and error-prone (Yadav & Singha, 2020). The difficulty in classifying student faces quickly can result in a variety of problems, such as wasted time, errors in recording attendance, and potential security threats (Childs & Lofton, 2021). The low efficiency and accuracy of facial recognition systems can interfere with the teaching and learning process and reduce comfort and safety in the campus environment (AbdELminaam et al., 2020).

This research overcomes the problem by applying the centroid and geometric mean methods in facial recognition. The centroid method determines the center point of the facial data (Varshney et al., 2024), while the geometric mean determines the optimal average distance for recognition (He et al., 2020). The students' facial data was analyzed using both methods to assess accuracy and speed. Implementation at STMIK YMI Tegal improves attendance management and campus security. The automatic facial recognition system ensures accurate and real-time student record-keeping, reducing administrative workload and manual attendance errors. The increased accuracy and reliability of these methods reinforce campus security with limited access for authorized individuals, creating a safer and more efficient environment.

Previous research relevant to the use of centroid and geometric averaging methods in facial recognition includes studies demonstrating their efficacy in feature extraction and pattern recognition. Previous research (Zhang et al., 2020), did not explore centroid methods in educational settings. Another study (St, 2022), also lacks focus on the use and comparison of the two methods in relevant contexts. Subsequent studies (Ijmtst, 2022), recognizing the effectiveness of geometric mean in different lighting conditions, they did not combine it with other methods to overcome environmental variations. Previous research (Andrejevic & Selwyn, 2020), discusses facial recognition optimization but does not explore the combination of centroid and geometric mean for improved facial recognition in devices with limited resources. Other studies (Conde López et al., 2022), show good accuracy compared to conventional optimization methods, but their application in real cases with complex error factors needs further investigation. Previous research has examined both methods in the context of improving recognition accuracy and computational efficiency. However, a comprehensive comparison of the two methods across diverse and challenging facial recognition studies has yet to be explored. This study seeks to expand the basic study by systematically evaluating the performance of centroid and geometric mean methods across various lighting, poses, and demographic variations, thus providing deeper insights and filling critical gaps in the existing literature.

Facial recognition methods that utilize centroid and geometric averaging techniques fill gaps in the literature by providing practical and efficient solutions, especially for institutions with limited resources such as STMIK YMI Tegal. This research highlights innovations in the application of simple and efficient methods that have not been widely applied in academic contexts. Both methods were chosen because of their ability to balance computing efficiency with high accuracy, according to the needs of the institution. Its implementation at STMIK YMI Tegal will improve campus attendance management and security, providing a cost-effective and robust solution that suits the specific needs of the institution.

2. RESEARCH METHOD

Research Design

This study used a combination design of experimental methods, quantitative analysis, and model validation. The experimental design was used to collect facial data from STMIK YMI Tegal environment, while quantitative analysis was used to process and analyze the data. Model validation is performed to ensure consistent and reliable performance of both methods. The research flow can be seen in figure 1.

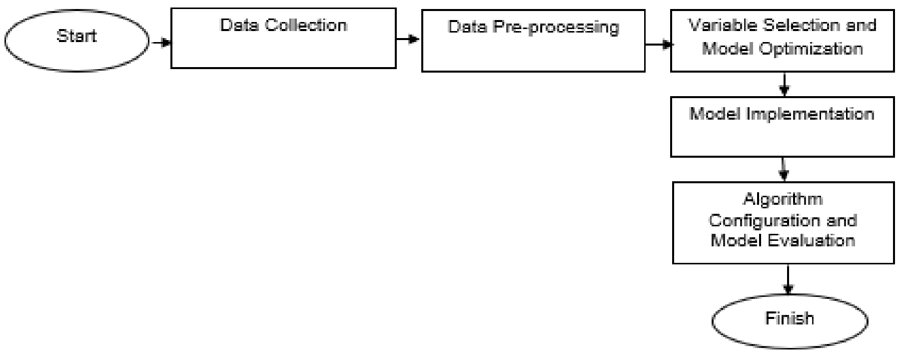

Figure 1. Research flow

Based on figure 1 explained The research flow began with data collection in the form of facial images of STMIK YMI Tegal students and non-student facial images as many as 20 respondents using the Vivo V27e camera with a resolution of 1092x1092 pixels which was then converted into 512x512 pixels. Furthermore, pre-processing of data is carried out by face detection, size and orientation adjustment, normalization of pixel intensity, conversion to grayscale, as well as calculation of mean and standard deviation for histogram creation. Then the relevant variables are selected and the research model is optimized to obtain accurate facial recognition results. After that, centroid and geometric mean methods are configured and implemented on the student face image dataset. The last stage is the completion of the research process of applying the two methods to facial recognition of STMIK YMI Tegal students.

Data Collection

The research data can be seen in figure 2.

Figure 2. Research data

In figure 2 shows the source of the research data used, namely the facial image of STMIK YMI Tegal students and the facial image of non-students. This data was obtained by making an acquisition using the Vivo V27e camera with a resolution of 1092x1092 pixels at a distance of 75 cm to 20 correspondent faces, where each correspondent was photographed once. The resulting facial image is then resized to 512x512 pixels to speed up the calculation process at a later stage. Specifically showing visual samples of collected facial images and will be used as datasets in research on the application of centroid and geometric mean methods for the facial recognition system of STMIK YMI Tegal students.

Data Pre-processing

The collected facial data is then pre-processed to ensure good quality and consistency. Pre-processing steps include face detection, size and orientation adjustment, and pixel intensity normalization to reduce the impact of lighting differences. Figure 3 shows the results of converting facial images to grayscale to facilitate the next process.

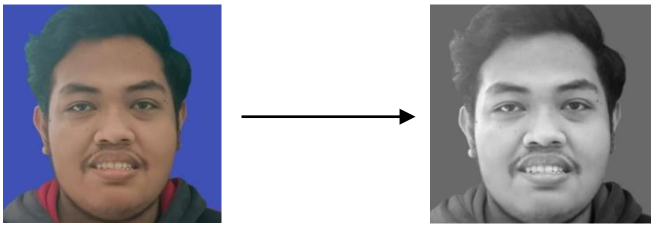

Figure 3. Convert image to face grayscale

Figure 3 shows the process of converting facial images to grayscale which is carried out as one of the stages of data pre-processing in research. This process aims to simplify the next stage by using functions from Python. The conversion to grayscale was done to reduce the complexity of the data and focus on light intensity information only, because color information is not very relevant in the face recognition process. This process is one of the important steps in pre-processing facial image data to prepare the data before further processing using centroid and geometric mean methods. Figure 4 shows a graph of histogram results.

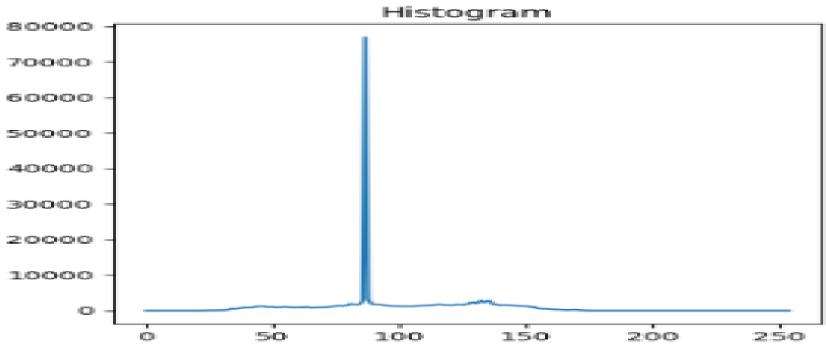

Figure 4. Chart histogram

Figure 4 shows a graph of a histogram resulting from the pre-processing process of facial image data. The histogram represents the pixel intensity distribution of the pre-converted grayscale image. The horizontal axis on the graph shows pixel intensity values, ranging from 0 (black) to 255 (white), while the vertical axis represents the number of pixels that have a specific intensity value. This histogram graph provides a visual representation of the distribution of pixel intensity values in the image, which will help in performing statistical calculations such as mean and standard deviation. This statistical information is important for the next stage in applying centroid and geometric mean methods in the facial recognition process of STMIK YMI Tegal students.

Variable Selection and Model Optimization

In this study, several important variables were considered including the accuracy of facial recognition, the speed of the recognition process, as well as the system's tolerance to variations in facial expressions, differences in lighting conditions, and camera viewing angles when taking facial images. To achieve optimal performance, the developed facial recognition model will be optimized by tuning certain parameters. This parameter tuning technique aims to improve the accuracy and generalizability of the model in recognizing faces with various conditions and characteristics.

Algorithm Implementation

The flow of research methods can be seen in figure 5.

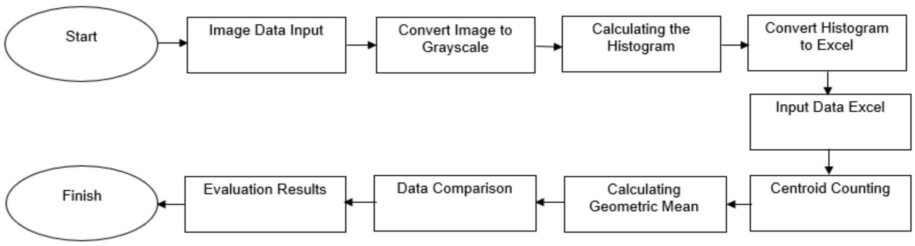

Figure 5. Research method flow

In figure 5 explain the flow of centroid and geometric mean methods in facial recognition of STMIK YMI Tegal students. This process starts with the input of image data, which is then converted to grayscale format for ease of processing. Next, the histogram of the image is calculated and this histogram data is converted into excel format. The data from excel is then fed back into the system for centroid and geometric mean calculations. Centroid is the central point of a set of data or objects (Yang & Han, 2020), which is formulated as follows:

```
centroid_x = data['Mean'].mean()
centroid_y = data['Standard Deviation'].mean()
```
(1)

Where, centroid_x is the mean of the mean column and centroid_y is the mean of the standard deviation column (Xiao et al., 2023). Meanwhile, geometric mean is a type of average that is calculated by multiplying all data values and then taking the power root n of the result of that multiplication, where n is the number of data values (Townshend et al., 2021), which is formulated as:

```
geometric_mean_x = np.exp(np.mean(np.log(data['Mean'] + 1)))
geometric_mean_y = np.exp(np.mean(np.log(data['Standard Deviation'] + 1)))
```
(2)

Where, add the value 1 to avoid problems with a value of 0 or negative for logarithms (Ab Wahab et al., 2021). Once the data is analyzed, the results are compared with pre-existing standards or data for evaluation. This process ends with an evaluation of the results that determines the accuracy and effectiveness of the methods used.

Evaluation of Results

The algorithms will be configured with appropriate parameters and will be evaluated using relevant metrics, such as accuracy, recall, precision, and F1-score. Accuracy is the ratio of the number of correct predictions to the total number of predictions (Sundararaman et al., 2022), which is formulated as:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{3}$$

Where, True Positive (TP) is the number of correct positive predictions, True Negative (TN) is the number of correct negative predictions, False Positive (FP) is the number of false positive predictions, False Negative (FN) is the number of false negative predictions (Poměnková & Malach, 2023). Precision measures the ratio of the number of correct positive predictions to the total number of positive predictions (Gavriilaki & Brodsky, 2020), formulated as:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{4}$$

Where, True Positive (TP) is the amount of data that is actually positive and predicted positive by the model and False Positive (FP) is the amount of data that is actually negative but predicted to be positive by the model (Verschae & Bugueno-Cordova, 2023). Recall, or sensitivity, is the ratio of the number of positive correct predictions to the total number of data that are actually positive (Bhangoo et al., 2022), with the formula:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{5}$$

Where, True Positive (TP) is the amount of data that is actually positive and predicted positive by the model and False Negative (FN) is the amount of data that is actually positive but predicted to be negative by the model (Smith & Miller, 2022). The F1-score is a harmonized average of precision and recall, giving a balanced picture of model performance (Chicco & Jurman, 2020), formulated as:

$$\text{F1} - \text{Score} = 2\,\text{X}\,\frac{\text{Precision}\,\text{X}\,\text{Recall}}{\text{Precision}\,\text{X}\,\text{Recall}} \tag{6}$$

Wherein, accuracy is the ratio of the number of correct predictions to the total number of predictions (Sundararaman et al., 2022), and recall or sensitivity is the ratio of the number of correct positive predictions to the total number of data that are actually positive (Cook & Ramadas, 2020). Model evaluation will be performed using validation data that is not used in the training process to ensure objective and accountable performance.

3. RESULTS AND DISCUSSIONS

At this stage, explain the series of results and discussion of the research conducted with the aim of applying and comparing the performance of centroid and geometric mean methods in facial recognition in the STMIK YMI Tegal environment. The results of the trial evaluation concluded the advantages and disadvantages that exist so that they can be developed again in order to improve this software. Table 1 is the display of image pre-processing results to grayscale which will later display images with numerical results.

Table 1. Image pre-processing results to grayscale

No	Image Data	Mean	Standar Deviation
1		114.334792	48.980428033212775
2		93.047264	27.6136752735724
3		114.56942	48.63992661244052
4		93.993044	35.857668909370894
5		97.507004	47.35787519456488

Table 1 shows five samples of facial imagery that have been converted from color to grayscale format from 20 samples of facial imagery, along with the average value (mean) of pixel intensity of each imagery. This mean value is one of the features to distinguish faces in the recognition process, where the more different the mean value between two images, the easier it is to distinguish them and provide a visual picture of grayscale conversion results as well as numerical information that will be converted to excel data. Furthermore, table 2 shows the conversion of grayscale data into Excel format that can be further processed.

Table 2. Convert grayscale to excel data

No	Image	Mean	Standard_Deviation
1	Farkhan	97.507.004	4.735.787.519.456.480
2	Surur	99.299.964	3.359.741.135.264.290
3	Khusni	117.466.672	4.869.533.276.654.360
4	Errika	113.521.088	30.139.680.212.242.700
5	Aries	11.456.942	4.863.992.661.244.050
6	Isna	93.993.044	35.857.668.909.370.800
7	Ambar	93.047.264	276.136.752.735.724
8	Adit	114.334.792	48.980.428.033.212.700
9	Ubay	9.795.636	2.931.331.246.294.760
10	Rohman	89.004.672	3.600.822.908.964.580
11	Ninik	19.903.794.917.076.100	37.181.175.384.193
12	Tiara	6.401.206.140.350.870	46.836.389.333.719.200
13	Iqbal	10.433.941.387.559.800	52.740.000.994.687.200
14	Ayu	12.667.678.685.897.400	6.407.652.254.608.390
15	Surya	7.346.268.427.518.420	3.911.605.190.939.630
16	Widya	10.370.956.303.139.300	7.081.115.205.779.720
17	Affan	9.843.068.107.578.390	387.160.757.142.403
18	Abdul	8.721.246.055.399.710	52.976.288.474.108.400
19	Erry	17.424.272.208.883.500	4.525.088.525.763.700
20	Lingga	10.135.936.073.059.300	646.752.264.780.501

Table 2 displays numerical data from 20 student facial images that have been converted to grayscale. Data is in the form of the average value (mean) and standard deviation of pixel intensity for each facial image. The numerical data will be used as input to apply centroid and geometric mean methods in facial recognition of STMIK YMI Tegal students based on image statistical characteristics. Next, table 3 shows the test data results.

Table 3. Data test results

No	Mean	Standar_deviation
1	97507004	4735787519456480
2	99299964	3359741135264290
3	117466672	4869533276654360
4	113521088	30139680212242700
5	11456942	4863992661244050

Table 3 shows the average value and standard deviation of the pixel intensity of grayscale facial images as input, as well as the results of centroid and geometric mean method calculations that will be evaluated using accuracy, precision, recall, and F1-score metrics by comparing predictions against actual data to analyze the performance of both methods in facial recognition of STMIK YMI Tegal students. Furthermore, table 4 displays the calculation results of the centroid method.

Table 4. Centroid method calculation results

Method	Mean	Standard Deviation
Centroid	30.0	4.0

Table 4 shows the results of the centroid method calculation on the face image dataset for facial recognition of STMIK YMI Tegal students. The centroid method produces a mean value of 30.0 and a standard deviation of 4.0 from the pixel intensity features of facial imagery in the dataset. This value is used as a reference in comparing the image of the face you want to recognize with the centroid dataset, where the proximity of the distance indicates similarity to the dataset. These results can be evaluated and compared with other methods such as geometric mean to assess performance in facial recognition. Furthermore, table 5 displays the results of the centroid method evaluation.

Table 5. Centroid method evaluation results

Method	Accuracy	Precision	Recall	F1-Score
Centroid	70.00%	75.00%	60.00%	66.67%

Table 5 displays the results of the centroid method evaluation by showing an accuracy value of 70%, precision 75%, recall 60%, and F1-score of 66.67%. These results provide an overview of the performance of the centroid method that can be analyzed and compared with other methods to determine the optimal approach in the facial recognition system in the campus environment. Furthermore, figure 6 displays a graph of the evaluation results of the centroid method.

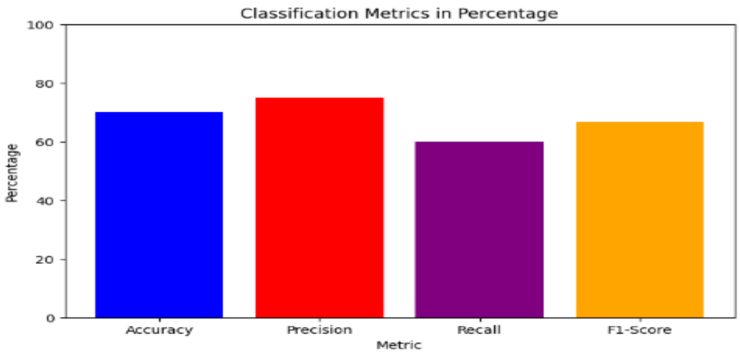

Figure 6. Centroid method evaluation results graph

Figure 6 represents the performance evaluation of the centroid method through a graph showing an accuracy value of 70%, precision 75%, recall 60%, and F1-score of 66.67%. This visualization allows further analysis on the strengths and weaknesses of the centroid method as well as its comparison with the geometric mean method in optimizing facial recognition systems in the campus environment. Furthermore, table 6 displays the calculation results of the geometric mean method.

Table 6. Results of geometric mean method calculation

Method	Mean	Standar Deviation
Geometric Mean	19.274859657043464	3.9148676411688634

Table 6 shows the results of calculating the geometric mean method on the face image dataset for facial recognition of STMIK YMI Tegal students. This method yields an average value (mean) of 19.274859657043464 and a standard deviation of 3.9148676411688634 from the pixel intensity features of face imagery in the dataset. These values are used as a reference in comparing the similarity of the tested facial image to the dataset, where close proximity indicates a high probability of being identified as part of the dataset. Furthermore, table 7 displays the results of the evaluation of the geometric mean method.

Table 7. Results of geometric mean method evaluation

Method	Accuracy	Precision	Recall	F1-Score
Geometric Mean	70.00%	75.00%	60.00%	66.67%

Table 7 shows the results of the evaluation of the geometric mean method with an accuracy of 70%, precision 75%, recall 60%, and F1-score of 66.67%. Accuracy indicates the overall percentage of correct predictions, precision represents the percentage of correct positive predictions, recall represents the percentage of positive data successfully recognized, while F1-score provides a harmonized average value of precision and recall as a measure of overall performance. These results allow analysis of the strengths and weaknesses of the geometric mean method and its comparison with the centroid method to optimize the student's facial recognition system. Next, figure 7 displays a graph of the results of the evaluation of the geometric mean method.

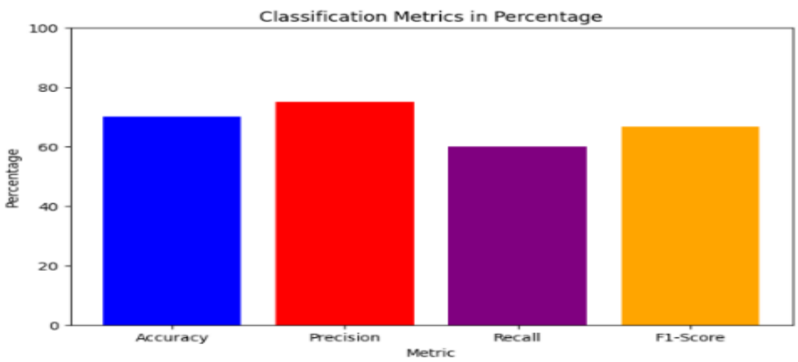

Figure 7. Graph of geometric mean method evaluation results

Figure 7 displays a graph of the evaluation results of the geometric mean method with an accuracy of 70%, precision 75%, recall 60%, and F1-score of 66.67%. This visualization facilitates the analysis of the strengths and weaknesses of the geometric mean method and its comparison with the centroid method to optimize the student facial recognition system.

The current research builds on and expands on previous studies on facial recognition by providing a more detailed and comparative analysis of centroid and geometric averaging methods. While previous research has highlighted the potential of these methods to improve recognition accuracy and resilience, there is often no comprehensive evaluation across conditions such as various lighting, face orientation, and demographic diversity. The study successfully filled the gap by systematically assessing the performance of both methods in various scenarios. This study provides evidence that student facial recognition can be applied and compared using simpler methods, namely centroid and geometric mean. Student facial image data is processed by pre-processing such as grayscale conversion. Both methods are implemented on the dataset and evaluated using accuracy, precision, recall, and F1-score metrics.

4. CONCLUSION

This study classifies and compares centroid and geometric average methods in students' facial recognition systems, with the same performance: 70% accuracy, 75% precision, 60% recall, and 66.67% F1-score. Practical implications include increased security, automation of attendance logging, and commercial applications. Contributions to science include algorithm development, the use of local datasets, and comprehensive performance evaluations. Both methods can be applied in academic environments with limited resources. Further research is recommended to optimize parameters, combine other techniques, and evaluate systems under various conditions.

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