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# Identification of fingerprint image with Minkowski distance algorithm approach

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ABSTRACT

In the digital era, fingerprint identification plays a critical role in information technology administration. Various studies have been conducted to improve the fingerprint identification process, but there are still cases of identification failures that are fatal. This research discusses fingerprint identification with the Minkowski distance method. The data of fingerprint are taken from Mathematics students and the Kaggle site. Data analysis includes the steps of image retrieval, dimensioning, conversion to gray scale, pattern matching, and accuracy measurement. Results show an improvement in data accuracy with a structured approach to data capture and preprocessing. Results from primary data obtained an accuracy of 56.67% while from secondary data obtained an accuracy of 93%.



## Introduction

The rapid growth in technology and information systems in the digital age is undergoing significant changes. Easy access to information through the internet has become a primary need, but the increasing use of digital technology also brings the risk of increased threats to security. Therefore, it is important to prioritize digital security protection that includes aspects of personal data protection, network security, and information system security(Gani, n.d.; Mayamin & Usuluddin, 2023; Nuriadin et al., 2021; Nuriadin, 2021).

Fingerprint sensors, as part of management information systems, play a role in the management of personal information. In the digital age, technological advancements impact on the vulnerability of information security. In the digital financial sector, this poses a threat of loss of assets or leakage of customer data, requiring simple and valid identification. Fingerprint sensors have several advantages, such as simplifying the identification process and data storage, while increasing the security of personal information(Emelda, n.d.; Rizaldi et al., n.d.; Nurliza & Widodo, 2018).

Fingerprint identification can be used to improve security and prevent data leakage. A study conducted by Satria et. al. (2017) showed that the fingerprint system can prevent personal data leakage up to 99.9%. In addition, another study conducted by Arifandi (2023) showed that a door security system using fingerprints based on Arduino Uno ATMega328 and SMS Gateway can identify residents of the house and provide solutions to homes left by their owners. In the study, the test results show access to open the door using fingerprints from outside can run well and homeowners can easily get information when someone breaks into the door by force (Arifandi, 2019; Aziz, n.d.; Gusri et al., n.d.; Hartono et al., 2023; Hermawan et al., 2023).

Various methods can be used in fingerprint identification, one of which is the Minkowski distance. The Minkowski distance method acts as an important metric for vector spaces, serving as a norm in the space, encompassing the generalized forms of Euclidean and Manhattan distances. The use of Minkowski distance in the fingerprinting approach contributes to the formation of a unique signature, ensuring a distinctive and non-copyable identification. This methodology, which is an integral part of vector space analysis, highlights the precision and complexity essential for robust applications, making it a key element in a collection of advanced techniques in the domain of data science and pattern recognition(Nurliza & Widodo, 2018; Pradana, 2017; Safwandi & Muthmainnah, n.d.).

Research that adopts the Minkowski distance method to perform distance analysis between data points in vector space can result in a deeper understanding of the structure and distribution of the data, open up the potential for discovering relevant patterns, and improve the accuracy of the analysis in the context in question. The Minkowski distance method is a very suitable method for translating distance analysis between data points, because it provides flexibility and generalization in measuring distance. The steps of this research involve calculating distance using the Minkowski distance formula to describe the relationships and patterns that exist in the data(Khairunnisa et al., n.d.; Nishom, 2019; Safwandi & Muthmainnah, n.d.; Thant & Aye, 2020).

## Method

This research adopting the Minkowski distance method to perform distance analysis between data points in vector space can lead to a deeper understanding of the structure and distribution of the data, open up the potential for discovering relevant patterns, and improve the accuracy of the analysis in the context in question. The Minkowski distance method is a very suitable method for translating distance analysis between data points, as it provides flexibility and generality in measuring distance. The steps of this research involved calculating distances using the Minkowski distance formula to illustrate the relationships and patterns present in the data.

### Data collection methods

*Experiment research*

In the data collection process, primary data was used by randomly collecting 30 fingerprints from students of the mathematics study program at Ahmad Dahlan University. In addition, an additional 6 reference data were also obtained to be included in the calculation of the Minkowski distance method. This method requires reference data as a reference in measuring the distance between primary data. Thus, the fingerprint data collected from these students will be analyzed using the Minkowski distance method by considering the 6 references data that have been previously determined. This aims to enable proper comparison between the primary data and the reference data, thus facilitating an accurate analysis process in the context of the Minkowski distance method.

*Literature study*

The data used in this research is secondary data obtained from the Kaggle platform. The data

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retrieval process was carried out with respect to the distance in which the photos were taken and involved cropping the data. This approach allows for a more structured selection and customization of data from such secondary sources to support proper analysis in a pre-defined method.

**Techniques for analyzing data**

Data analysis is an essential component of the research framework. The reliability of resolving the issues in focus and the conclusions that result from a study have a substantial dependence on the integrity and completeness of the data analysis conducted. The analysis methods and procedures applied in this study included the following steps.

*Fingerprint image capture*

At this stage, 36 images are taken, consisting of 6 fingerprint reference templates (guide1.jpg - guide6.jpg) and 30 input templates to be tested (finger.1.jpg - finger.30.jpg). Subsequently, these images are stored for further processing.

*The process of customizing the image dimensions to* $4 \times 4$ *pixels*

This step is designed to normalize the input image to be analyzed.

*Image conversion from RGB color mode to grayscale*

This is necessary so that the image can be processed using the chosen method.

*Pattern matching*

In this phase, processing is performed between the reference sample template and the input template that has been taken. Each template, be it the reference image or the cropped input image, is analyzed comparatively one by one. To assess the similarity between the two templates, the Minkowski distance method is used. This method calculates the distance value between the two templates being compared. An input template will be classified as similar to the reference template if the distance value between the two is equal to, or less than 30.

*Accuracy measurement*

In this step, the accuracy of the Minkowski distance method will be evaluated to determine whether or not this method is suitable in the template matching process (See Figure 1).

**Minkowski distance method and accuracy technique**

The Minkowski Distance method has a formula that integrates the characteristics of Euclidean Distance and Manhattan Distance with p as a parameter. When the value of $p = 1$, it has the same formula as Manhattan Distance, while if $p = 2$, the formula tends to be Euclidean Distance. The general formula of Minkowski Distance is,

$$d(x, y) = (\sum_{i=1}^{n} |x_i - y_i|^p)^{\frac{1}{p}} \tag{1}$$

The calculation process to evaluate the accuracy of a method or procedure that has been implemented (See Figure 1). This accuracy analysis aims to measure the extent to which the results obtained are in accordance with the expected standards or meet predetermined criteria. This stage makes it possible to identify the advantages and disadvantages of a method or technique used in the context of data processing or analysis being carried out. The general formula for accuracy is,

$$Accuracy(\%) = \frac{\sum many\ successes,}{\sum total\ number\ of\ data} \times 100\%$$

(2)

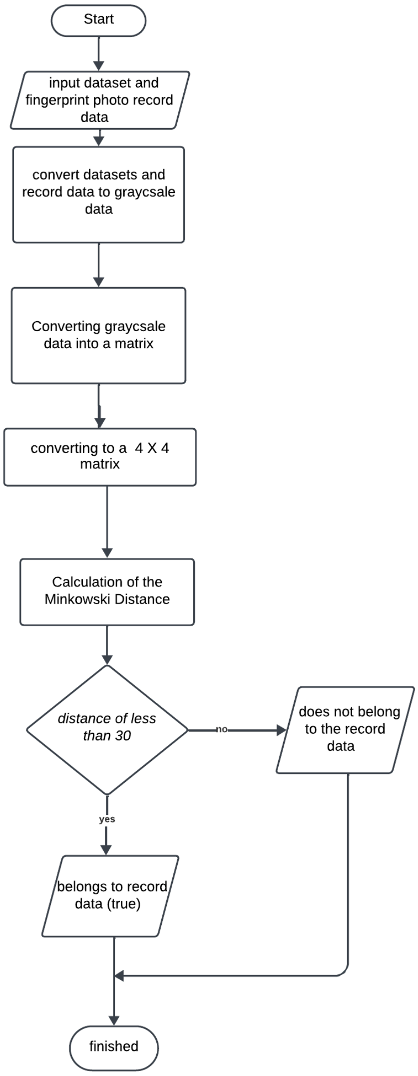


**Figure 1.** Minkowski distance method flowchart

## Results and discussion

The data that has been taken is then converted into a matrix in the RGB color scheme, then converted into a grayscale matrix. Furthermore, from the initial matrix that has a size of $m \times m$, dimensional adjustments are made to a $4 \times 4$ matrix (See Figure 2). This step aims to minimize the dimensions of the data so that it can be processed more efficiently and in accordance with the predetermined analysis needs.

Matrix P1 refers to the matrix derived from guideline 1. Using the established definition of 1, the Minkowski distance will be calculated for the matrix. This process is part of the evaluation of the similarity or difference between the reference matrix and other matrices within the framework of the predefined method.


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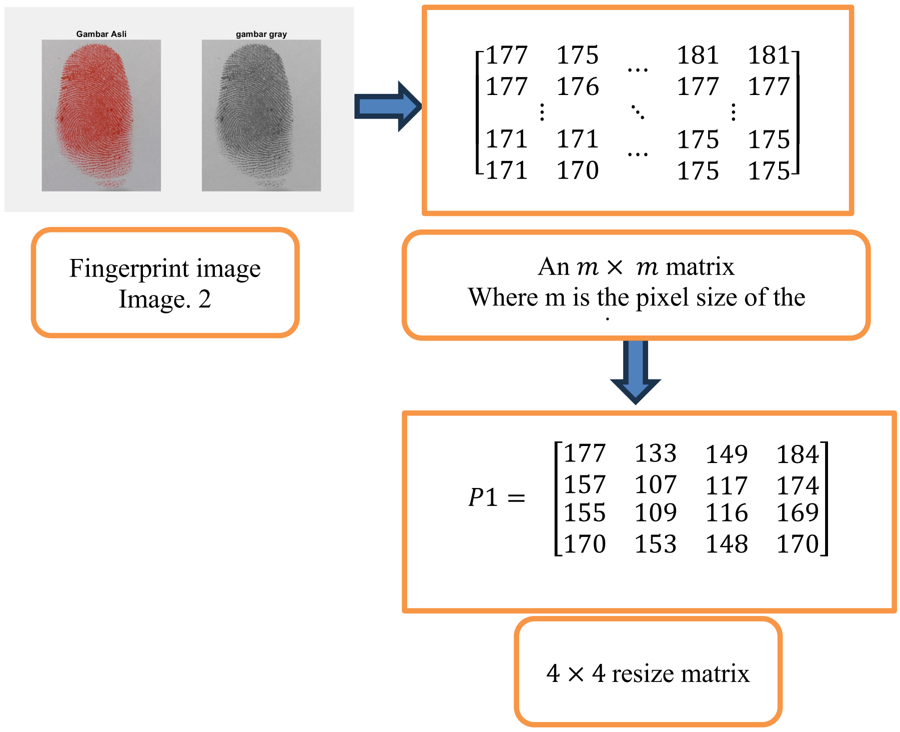


**Figure 2.** Processing fingerprint data into 4 × 4 matrix

Manual calculation as follows. Comparison of respondent 1 with guideline 1 results:

$$R1 = \begin{bmatrix} 177 & 144 & 132 & 172 \\ 148 & 91 & 92 & 144 \\ 127 & 83 & 91 & 140 \\ 146 & 114 & 129 & 161 \end{bmatrix}$$

$$P1 = \begin{bmatrix} 177 & 133 & 149 & 184 \\ 157 & 107 & 117 & 174 \\ 155 & 109 & 116 & 169 \\ 170 & 153 & 148 & 170 \end{bmatrix}$$

$$p = 3$$

$$d(x, y) = (|177 - 177|^3 + |133 - 144|^3 + |149 - 132|^3 + \cdots + |170 - 161|^3)^{\frac{1}{3}}$$
$$d(x, y) = 59.9717459564981$$

With a similar approach, calculations were made using Guideline 1 to Guideline 6 against the responses from Respondent 1 to Respondent 30. This step was carried out to analyze and evaluate the suitability and similarity between each guideline and the respective responses generated by the respondents involved in this study and the following Table 1 was obtained.

**Table 1.** Calculation on data from respondents based on Guideline 1 to 6

| Number | Name | Guidelines 1 | Guidelines 2 | Guidelines 3 | Guidelines 4 | Guidelines 5 | Guidelines 6 | Classification Results | Success |
|---|---|---|---|---|---|---|---|---|---|
| 1 | Respondent1 | 59,9717 | 68,1699 | 37,9984 | 82,7347 | 50,2466 | 61,2808 | Does not belong to guideline data | works |
| 2 | Respondent2 | 80,7384 | 89,8481 | 78,3769 | 90,3676 | 69,093 | 63,3747 | Does not belong to guideline data | works |
| 3 | Respondent3 | 65,6447 | 71,2493 | 91,7409 | 46,9907 | 63,0258 | 42,7467 | Does not belong to guideline data | works |
| 4 | Respondent4 | 71,4142 | 69,0025 | 76,1025 | 64,2724 | 60,185 | 54,4752 | Does not belong to guideline data | works |
| 5 | Respondent5 | 96,3032 | 92,7073 | 128,6952 | 65,8542 | 104,6089 | 93,5718 | Does not belong to guideline data | works |
| 6 | Respondent6 | 37,9037 | 32,4189 | 58,3379 | 36,4415 | 53,6541 | 50,5340 | Does not belong to guideline data | works |
| 7 | Respondent7 | 50,2726 | 38,0567 | 56,3271 | 44,8584 | 46,5402 | 46,7214 | Does not belong to guideline data | works |
| 8 | Respondent8 | 34,2930 | 46,8687 | 56,3271 | 55,9647 | 35,2389 | 35,4968 | Does not belong to guideline data | works |
| 9 | Respondent9 | 43,4746 | 56,2209 | 34,6287 | 73,2616 | 45,2215 | 54,5415 | Does not belong to guideline data | works |
| 10 | Respondent10 | 31,7185 | 33,2918 | 59,3669 | 23,3059 | 34,8326 | 32,6972 | Belonging to the guideline data | Failed |
| 11 | Respondent11 | 23,4329 | 29,3833 | 30,1338 | 49,452 | 36,4162 | 45,4339 | Belonging to the guideline data | Failed |
| 12 | Respondent12 | 35,6585 | 40,1306 | 46,5394 | 38,8048 | 23,3915 | 26,167 | Belonging to the guideline data | Failed |
| 13 | Respondent13 | 101,2387 | 109,2219 | 98,0335 | 113,9386 | 23,3915 | 26,167 | Belonging to the guideline data | Failed |
| 14 | Respondent14 | 33,0653 | 42,1691 | 30,5394 | 57,085 | 31,9056 | 40,4521 | Does not belong to guideline data | works |
| 15 | Respondent15 | 42,2666 | 41,9367 | 68,8864 | 14,8639 | 40,2352 | 32,2301 | Belonging to the guideline data | Failed |
| 16 | Respondent16 | 45,1987 | 51,9454 | 47,6481 | 55,3524 | 29,1376 | 24,744 | Does not belong to guideline data | Failed |
| 17 | Respondent17 | 43,6056 | 45,9337 | 36,3201 | 51,611 | 22,3551 | 29,9599 | Belonging to the guideline data | Failed |
| 18 | Respondent18 | 39,5631 | 48,1102 | 56,5746 | 44,2941 | 37,4866 | 32,3082 | Does not belong to guideline data | works |
| 19 | Respondent19 | 29,9803 | 48,1102 | 56,5746 | 44,2941 | 37,4866 | 32,3082 | Belonging to the guideline data | Failed |
| 20 | Respondent20 | 37,7057 | 34,6576 | 50,2614 | 35,9368 | 20,8415 | 22,1171 | Belonging to the guideline data | Failed |
| 21 | Respondent21 | 57,8054 | 58,2673 | 85,166 | 24,6242 | 52,5613 | 39,5156 | Belonging to the guideline data | Failed |
| 22 | Respondent22 | 33,0214 | 38,0454 | 42,7767 | 42,3725 | 25,4195 | 33,7773 | Belonging to the guideline data | Failed |
| 23 | Respondent23 | 41,4974 | 39,9628 | 66,8592 | 15,9634 | 38,21804 | 27,63034 | Belonging to the guideline data | Failed |
| 24 | Respondent24 | 51,0921 | 51,1571 | 79,7653 | 23,55 | 47,6627 | 33,2665 | Belonging to the guideline data | Failed |
| 25 | Respondent25 | 46,7772 | 45,2199 | 53,8587 | 43,587 | 29,7007 | 25,993 | Belonging to the guideline data | works |
| 26 | Respondent26 | 46,7772 | 45,2199 | 53,8587 | 43,5870 | 29,7007 | 23,3426 | Belonging to the guideline data | works |
| 27 | Respondent27 | 45,9274 | 50,9755 | 41,5662 | 59,5204 | 27,3462 | 30,4041 | Belonging to the guideline data | works |
| 28 | Respondent28 | 38,5918 | 42,7663 | 66,9229 | 20,397 | 37,2382 | 22,8509 | Belonging to the guideline data | works |
| 29 | Respondent29 | 37,8877 | 26,0487 | 61,2362 | 21,6237 | 42,0035 | 39,996 | Belonging to the guideline data | works |
| 30 | Respondent30 | 40,7947 | 43,4481 | 65,8272 | 26,0928 | 35,2201 | 22,6753 | Belonging to the guideline data | works |

From the previously tested data, the accuracy and success of the tested image matching can be evaluated using the following methods.

$$Accuracy(\%) = \frac{\sum many\ successes,}{\sum total\ number\ of\ data} \times 100\%$$

$$Accuracy(\%) = \frac{17}{30} \times 100\%$$

$$Accuracy(\%) = 56{,}67\%$$

Then, we continue to analyze the following steps (See Figure 3). Matrix P1 refers to the matrix derived from guideline 1. Using the established definition of 1, the Minkowski distance will be calculated for the matrix. This process is part of the evaluation of the similarity or difference between the reference matrix and other matrices within the framework of the predefined method.

The manual calculation is as follows. Comparison of respondent1 with guideline 1.

$$R1 = \begin{bmatrix} 223 & 197 & 202 & 189 \\ 164 & 114 & 109 & 122 \\ 140 & 110 & 116 & 115 \\ 141 & 109 & 116 & 124 \end{bmatrix}$$

$$P1 = \begin{bmatrix} 230 & 210 & 210 & 191 \\ 215 & 119 & 107 & 170 \\ 194 & 119 & 112 & 170 \\ 160 & 94 & 108 & 149 \end{bmatrix}$$

$$p = 3$$

$$d(x,y) = (|230-223|^3 + |210-197|^3 + |210-202|^3 + \cdots + |149-149|^3)^{\frac{1}{3}}$$



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$$d(x,y) = 84.22309366304167$$

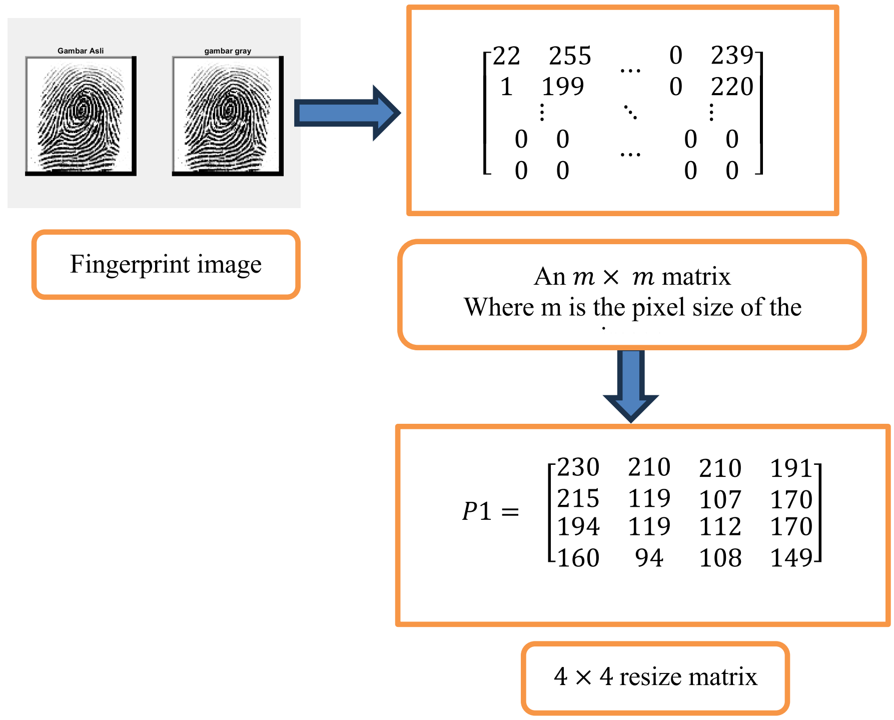


**Figure 3.** Further processing fingerprint data into $4 \times 4$ matrix

**Table 2.** Calculation on data from respondents based on Guideline 1 to 6

| Number | Name | Guidelines 1 | Guidelines 2 | Guidelines 3 | Guidelines 4 | Guidelines 5 | Guidelines 6 | Classification Results | Success |
|---|---|---|---|---|---|---|---|---|---|
| 1 | Respondent1 | 84,22 | 73,57 | 88,12 | 67,43 | 78,46 | 98,34 | Does not belong to guideline data | works |
| 2 | Respondent2 | 136,44 | 125,84 | 126,2 | 57,19 | 87,45 | 126,21 | Does not belong to guideline data | works |
| 3 | Respondent3 | 56,96 | 56,24 | 45,5 | 118,57 | 95,86 | 109,39 | Does not belong to guideline data | works |
| 4 | Respondent4 | 112,55 | 100,48 | 110,05 | 61,38 | 63,97 | 54,96 | Does not belong to guideline data | works |
| 5 | Respondent5 | 82,75 | 65,96 | 56,08 | 89,55 | 71,95 | 104,89 | Does not belong to guideline data | works |
| 6 | Respondent6 | 116,84 | 109,9 | 126,32 | 58,41 | 86,31 | 87,93 | Does not belong to guideline data | works |
| 7 | Respondent7 | 104,3 | 101,75 | 87,09 | 89,55 | 103,86 | 128,97 | Does not belong to guideline data | works |
| 8 | Respondent8 | 110,49 | 97,07 | 104,28 | 40,29 | 61,62 | 72,4 | Does not belong to guideline data | works |
| 9 | Respondent9 | 112,23 | 120,2 | 104,83 | 196,64 | 176,45 | 175,44 | Does not belong to guideline data | Failed |
| 10 | Respondent1( | 77,23 | 60,22 | 53,01 | 122,95 | 88,68 | 117,33 | Does not belong to guideline data | works |
| 11 | Respondent1: | 117,87 | 109,58 | 97,66 | 84,73 | 94,93 | 137,41 | Does not belong to guideline data | works |
| 12 | Respondent1; | 156,49 | 149,11 | 164,64 | 73,13 | 114,06 | 132,93 | Does not belong to guideline data | works |
| 13 | Respondent1: | 87,7 | 93,45 | 82,32 | 70,12 | 80,18 | 83,35 | Does not belong to guideline data | works |
| 14 | Respondent1‹ | 101,07 | 95,41 | 94,14 | 71,78 | 82,34 | 63,91 | Does not belong to guideline data | works |
| 15 | Respondent1! | 150,15 | 140,17 | 154,36 | 58,43 | 99,89 | 100,22 | Does not belong to guideline data | works |
| 16 | Respondent1( | 118,51 | 112,3 | 120,47 | 144,86 | 130,75 | 104,91 | Does not belong to guideline data | works |
| 17 | Respondent1: | 92,22 | 91,22 | 88,97 | 68,91 | 70,87 | 99,97 | Does not belong to guideline data | works |
| 18 | Respondent1{ | 84,01 | 86,58 | 81,35 | 71,84 | 89,03 | 108,71 | Does not belong to guideline data | works |
| 19 | Respondent1! | 87,14 | 62,28 | 71,4 | 94,48 | 22,25 | 68,25 | Belonging to the guideline data | works |
| 20 | Respondent2( | 65,68 | 47,94 | 68,85 | 90,81 | 48,82 | 83,8 | Does not belong to guideline data | works |
| 21 | Respondent2: | 112,01 | 94,76 | 110,85 | 79,91 | 58,23 | 55,23 | Does not belong to guideline data | works |
| 22 | Respondent2; | 115,32 | 107,19 | 111,48 | 38,59 | 79,1 | 82,58 | Does not belong to guideline data | works |
| 23 | Respondent2: | 154,11 | 140,82 | 137,74 | 75,4 | 108,51 | 156,37 | Does not belong to guideline data | works |
| 24 | Respondent2‹ | 104,02 | 98,42 | 91,38 | 75,17 | 91,59 | 131,26 | Does not belong to guideline data | works |
| 25 | Respondent2! | 137,45 | 124,63 | 128,49 | 39,47 | 95,98 | 130,64 | Does not belong to guideline data | works |
| 26 | Respondent2( | 71,03 | 71,34 | 81,29 | 70,24 | 69,37 | 77,69 | Does not belong to guideline data | works |
| 27 | Respondent2: | 120,82 | 101,72 | 120,31 | 58,49 | 54,13 | 56,14 | Does not belong to guideline data | works |
| 28 | Respondent2{ | 118,48 | 100,99 | 115,37 | 69,15 | 58,04 | 46,33 | Does not belong to guideline data | works |
| 29 | Respondent2! | 99,31 | 100,26 | 89,67 | 104,67 | 120,56 | 126,62 | Does not belong to guideline data | Failed |
| 30 | Respondent3( | 61,51 | 66,25 | 56,47 | 88,02 | 70,92 | 75,87 | Does not belong to guideline data | works |

With a similar approach, calculations were made using Guideline 1 to Guideline 6 against the responses from Respondent 1 to Respondent 30. This step was carried out to analyze and evaluate the suitability and similarity between each guideline and the respective responses generated by the respondents involved in this study and Table 2 was obtained.

From the previously tested data, the accuracy and success of the tested image matching can be evaluated using the following methods:

$$Accuracy(\%) = \frac{\sum many\ successes,}{\sum total\ number\ of\ data} \times 100\%$$

$$Accuracy(\%) = \frac{28}{30} \times 100\%$$

$$Accuracy(\%) = 93\%$$

From the results of the first data processing, an accuracy rate of 56.67% was obtained. While in the second data processing, the accuracy rate increased to 93%. This significant difference is due to the different approaches in data collection. In the first data collection, there was no consideration of the data collection distance or cropping process on the data set. In contrast, in the second data collection, a more structured approach was used with data collection at a uniform distance and the application of a cropping process, which resulted in a significant increase in data accuracy.

## Conclusion

The results of using the Minkowski Distance method on the first data showed an accuracy rate of 56.67%, which is significant but worth noting for further improvement. The use of the second data that considered the capture distance and applied cropping resulted in an increase in accuracy to 93%, confirming the importance of a structured approach to data capture. A suggestion for future research is to consider other factors that affect accuracy, such as variations in image capture angle or more complex preprocessing techniques. Further evaluation of these factors can help improve the accuracy of the method in fingerprint image recognition.

Suggestions for further research include several things that can be optimized. Firstly, it is recommended to consider the use of additional data to improve a greater level of accuracy in fingerprint recognition. Second, it is recommended to consider an approach to minimize the fingerprint image in certain parts of the diagram to obtain a more optimized matrix. Thirdly, it is recommended to further normalize the matrix to produce smaller values, simplifying the calculation process. Finally, it is important to pay attention to the pixel size when photographing fingerprint data, considering it as a key factor in image capture for more accurate analysis. With these suggestions in mind, future research is expected to make significant progress in the development of more reliable and efficient fingerprint recognition methods.

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