

# Comparison of Artificial Neural Network and Gaussian Naïve Bayes in Recognition of Hand-Writing Number

1<sup>st</sup> Herman

*Faculty of Computer Science*  
*Universitas Muslim Indonesia*  
Makassar, Indonesia  
herman@umi.ac.id

2<sup>nd</sup> Lukman Syafie

*Faculty of Computer Science*  
*Universitas Muslim Indonesia*  
Makassar, Indonesia  
lukman.syafie@umi.ac.id

3<sup>rd</sup> Dolly Indra

*Faculty of Computer Science*  
*Universitas Muslim Indonesia*  
Makassar, Indonesia  
dolly.indra@umi.ac.id

4<sup>th</sup> As'ad Djamilileil

*Faculty of Computer Science*  
*Universitas Muslim Indonesia*  
Makassar, Indonesia  
asad.kom@gmail.com

5<sup>th</sup> Nirsal

*Faculty of Computer Engineering*  
*Cokroaminoto Palopo University*  
Palopo, Indonesia  
nirsal-ftkom@uncp.ac.id

6<sup>th</sup> Heliawaty Hamrul

*Faculty of Computer Engineering*  
*Cokroaminoto Palopo University*  
Palopo, Indonesia  
heliawaty@uncp.ac.id

7<sup>th</sup> Siska Anraeni

*Faculty of Computer Science*  
*Universitas Muslim Indonesia*  
Makassar, Indonesia  
siska.anraeni@umi.ac.id

8<sup>th</sup> Lutfi Budi Ilmawan

*Faculty of Computer Science*  
*Universitas Muslim Indonesia*  
Makassar, Indonesia  
lutfibudi.ilmawan@umi.ac.id

**Abstract**—Current technological developments spur the application of pattern recognition in various fields, such as the introduction of signature patterns, fingerprints, faces, and handwriting. Human handwriting has differences between one another and often is difficult to read or difficult to recognize and this can hamper daily activities, such as transaction activities that require handwriting. Even though one of the human biometric features is handwriting. The purpose of this paper is to compare the algorithm of Artificial Neural Network (ANN) and Gaussian Naïve Bayes (GNB) in handwriting number recognition. Both of these algorithms are quite reliable in performing the classification process. ANN can do pattern recognition and provide good results. If the size of the training data is small, the accuracy of GNB provides good results. To recognize the handwriting pattern, the characteristics of the handwriting object are extracted using an invariant moment. The test results show that GNB produces a higher level of accuracy of 28.33% compared to the ANN of 11.67%. The resulting accuracy level is still very low. This is because the result extraction data has a small distance for each class or any number character.

**Keywords**—handwriting, ANN, GNB, moment invariant

## I. INTRODUCTION

An object has characteristics which are the properties of the object and a combination of these characteristics can be said to be a pattern. At present, developments in the field of computer science are very rapid, including pattern recognition. Pattern recognition of an object is a classification or depiction based on the main characteristics of the object. Application of pattern recognition can also be applied to distinguish or recognize objects based on the specific characteristics of the object. Current technological developments spur the application of pattern recognition in various fields, such as the introduction of signature patterns, fingerprints, faces, and handwriting.

In the field of computer vision, handwriting is a complex thing to recognize. Handwriting is unique to everyone.

Human handwriting has differences between one another and often handwriting is difficult to read or difficult to recognize and this can hamper daily activities, such as transaction activities that require handwriting. This can lead to costly and long-term expenses and will allow many mistakes to occur [1]. Computer vision has been widely used to recognize handwritten digits, such as reading bank check numbers [2]. Even one of the biometric characteristics in each person is handwriting, this is because everyone has a unique handwriting pattern [3].

The main purpose of number recognition or handwritten letters is to make the computer convert text images into text representations [4]. Many organizations or companies spend a lot of money, time and energy to convert paper data in the form of handwriting into computer data. This is done so that data can be processed or edited [1]. The recognition of numbers or handwritten letters is considered something that is difficult to do because of several factors, such as size and slope [4]. The first step to overcome this problem is character recognition or numeric letters on computer data. In the process of recognizing numeric characters or letters, several algorithms can be used. This algorithm includes the Artificial Neural Network and Naïve Bayes.

Research on handwriting has been carried out by [5]. The focus in the study was to segment Arabic handwriting characters. The same thing was done by [6], where in the study segmentation was carried out on handwriting in Hindi. In research [7] rearranging from Thai calligraphy. The study aims to rearrange the handwriting or calligraphy whose irregular arrangement becomes organized. Some of the studies that have been described have not carried out the introduction of letter or number characters. The purpose of this paper is to recognize and compare algorithms of Neural Networks and Naïve Bayes in handwriting number recognition. Both of these algorithms are quite reliable in performing the classification process. Artificial Neural Networks can do pattern recognition and provide good

results [1]. According to the results of research conducted by [8], if the size of the training data is small, the accuracy of Naïve Bayes provides good results. The experimental results show a high degree of accuracy from Naïve Bayes in conducting document orientation detection [9].

The next section of this paper is as follows. Section II describes the data, feature extraction methods, Artificial Neural Networks, and Gaussian Naive Bayes. Section III describes the test results of the two algorithms that are compared. Finally, conclusions based on the results of the tests are discussed in Section IV.

## II. METHOD

### A. Data

Image data processed in this study used a dataset from the Modified National Institute of Standards and Technology database (MNIST). This type of image is already in binary form so that it does not require preprocessing and segmentation anymore. The binary image has only two-color values: 0 for black and 1 for white.

The amount of data used is 200 data consisting of 20 data for each number character. Of the 200 data, 70% or 160 data or 16 data for each character is used as training data, while the rest is used as test data. Each data was trained and tested using Artificial Neural Network and Gaussian Naive Bayes to measure each algorithm in carrying out handwriting number recognition. The example of the processed image data is shown in Fig. 1.

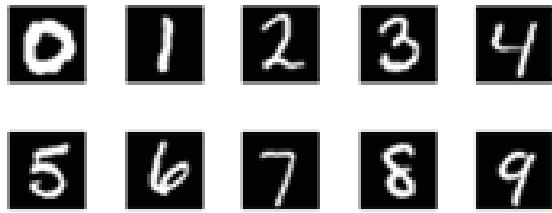


Fig. 1. Data image

In this study, outline consists of 2 parts, namely the training process and the testing process. Before the data goes through the training process, handwritten image data is extracted. The characteristic taken is the form of handwriting numbers in the image. The method used in performing feature extraction is the Moment Invariant. The flow of handwriting number recognition research can be seen in Fig. 2.

$$\phi_1 = \eta_{20} + \eta_{02}$$

$$\phi_3 = (\eta_{30} - 3\eta_{12})^2 + (\eta_{03} - 3\eta_{21})^2 \quad (1)$$

Data from feature extraction from the Moment Invariant is then used for the training and testing process. Results from the training process are saved to the database for use in the testing process. Artificial Neural Networks (ANN) and Gaussian Naïve Bayes (GNB) are used for training and testing processes to measure the accuracy of each method. The data used in the training process is 70% of the total data processed, while the testing process is 30%.

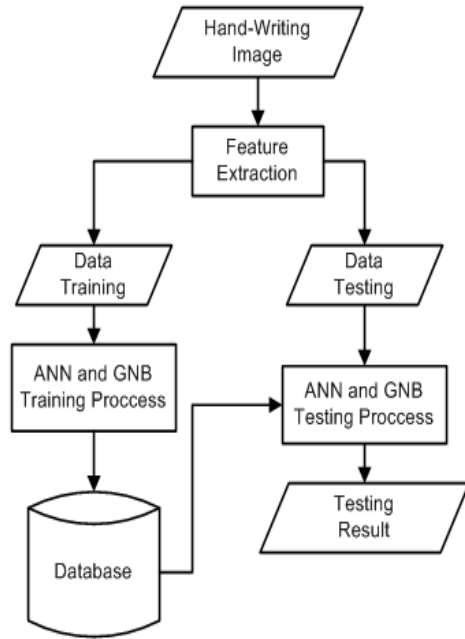


Fig. 2. Research flow

### B. Artificial Neural Network

The training and testing process uses Artificial Neural Network (ANN) with back-propagation learning algorithm. Back-propagation aims to minimize output error squares or algorithms that use weight adjustment patterns to achieve minimum error values. Artificial Neural Network provide good results in the introduction of complex patterns to get information from objects [1].

In the training process using ANN, first determine the parameters and values and training data. In addition to training data, the target value for each training data is also important because it becomes a reference in the training process. The ANN architecture used is shown in Fig. 3.

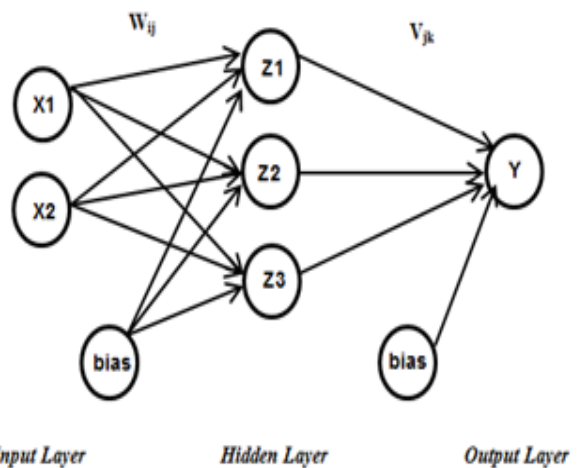


Fig. 3. ANN Architecture

### C. Gaussian Naïve Bayes

Bayes theorem, also known as Bayes rule, is a useful tool for calculating conditional probability. The conditional opportunity of A when B is denoted by P (A | B). Gaussian

distribution is one of the most common and important methods in calculating probability and statistics. Gaussian distribution is [10]:

$$P(x) = \frac{1}{\delta\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\delta^2}} \quad (2)$$

Where,  $\mu$  is the average and  $\delta$  is the standard deviation. To get the value of  $\mu$  and  $\delta$  used (3) and (4):

$$\mu = \frac{\sum_{i=1}^n xi}{n} \quad (3)$$

$$\delta^2 = \frac{\sum_{i=1}^n (xi-\mu)^2}{n-1} \quad (4)$$

Bayes theorem is stated in the following (5):

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \quad (5)$$

Where:

- P (A) and P (B) are probability A and B and independent
- P (A | B), probability A if B is correct
- P (B | A), probability B if A is correct

### III. RESULT AND DISCUSSION

In this study, the training was carried out by exploring the hidden layer of Artificial Neural Network (ANN). Exploration is done in the hidden layer with the number of neurons 10 to 100. The value of the correlation coefficient increases as the number of neurons in the hidden layer increases. The highest correlation coefficient value is obtained when using 30 neurons in the hidden layer with a value of 0.61382. Test results on artificial neural networks are shown in Table I.

TABLE I. TEST RESULT OF ANN

No.	Num. Of Neuron	Correlation Coefficient
1.	10	0,57619
2.	20	0,58146
3.	30	0,61382
4.	40	0,54183
5.	50	0,54686
6.	60	0,53271
7.	70	0,54586
8.	80	0,53218
9.	90	0,53195
10.	100	0,53171

From all exploration training conducted, the highest correlation coefficient is obtained when using 30 neurons in the hidden layer. Based on this, the test data was tested using ANN with parameters and values obtained from the training

using 30 hidden layer neurons. The level of accuracy obtained from the test results is 11.67% of the total test data.

Then continued testing using Gaussian Naïve Bayes. The accuracy obtained is 28.33% of the total test data. Table II shows the pieces result of the test using Gaussian Naïve Bayes (GNB).

Test results using ANN and GNB show the level of accuracy generated from GNB is higher than ANN. Although the level of accuracy of GNB is higher, but the expected level of accuracy is still small. This is because the extracted data has a small distance for each class or any number character.

TABLE II. TEST RESULT OF GNB (RR=RECOGNITION RESULT, RV=REAL VALUE, C=CONCLUSION)

0	1	...	9	Max	RR	RV	C
0.01268	0.045806	...	0.003726	0.170086	5	0	F
0.183935	0.076568	...	0.002689	0.183935	0	0	T
0.541946	0.353131	...	0.128779	0.541946	0	0	T
0.365704	0.189672	...	0.01269	0.365704	0	0	T
0.10884	0.018717	...	0.002292	0.138371	8	0	F
0.509432	0.256838	...	0.16003	0.509432	0	0	T
0.425815	0.402483	...	0.095479	0.425815	0	1	F
0.149137	0.255422	...	0.215245	0.343774	5	1	F
0.431275	0.30812	...	0.018259	0.431275	0	1	F
0.010098	0.039976	...	7.99E-06	0.039976	1	1	T
0.429321	0.188106	...	0.189414	0.52594	8	1	F
0.356126	0.382284	...	0.095142	0.382284	1	1	T
0.256005	0.091403	...	0.189031	0.485084	8	2	F
0.203819	0.288181	...	0.281778	0.318685	5	2	F
0.138424	0.240482	...	0.070469	0.325935	5	2	F
0.015011	0.067023	...	0.022706	0.282625	2	2	T
0.001217	0.014548	...	0.003535	0.200838	2	2	T
0.031645	0.121638	...	0.250926	0.413701	2	2	T
0.000787	0.019021	...	0.03478	0.288826	7	3	F
0.002307	0.030619	...	0.037086	0.288385	2	3	F
...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...
0.214783	0.147231	...	0.494004	0.820044	6	7	F
0.034795	0.064036	...	0.634167	1.117016	6	7	F
0.000737	0.018736	...	0.147127	0.352251	7	7	T
0.023984	0.008075	...	0.062253	0.138112	8	7	F
0.080611	0.024879	...	0.11468	0.282165	8	7	F
0.136795	0.022355	...	0.005915	0.198704	8	8	T
0.349048	0.112047	...	0.023311	0.349048	0	8	F
0.286584	0.106799	...	0.198467	0.502766	8	8	T
0.11178	0.220426	...	0.115946	0.347098	5	8	F

0	1	...	9	Max	RR	RV	C
0.278005	0.188498	...	0.460376	0.663935	6	8	F
0.047848	0.140077	...	0.457027	0.457027	9	8	F
0.109869	0.090958	...	0.539805	1.047337	6	9	F
0.433138	0.255067	...	0.285847	0.489112	8	9	F
0.050724	0.132751	...	0.580601	0.614456	6	9	F
0.059199	0.014683	...	0.064015	0.226378	8	9	F
0.206464	0.114036	...	0.392397	0.642227	6	9	F
0.000147	0.008036	...	0.012792	0.234472	7	9	F

#### IV. CONCLUSION

The test results show that the level of accuracy produced by Gaussian Naïve Bayes (GNB) is better than artificial neural networks. The level of accuracy generated by GNB is 28.33%, while ANN is 11.67%. The resulting accuracy level is very low and the cause is that the class distance between data is very small.

#### FUTURE SCOPE

For the sustainability of this research is to replace the feature extraction method or use all the features that are generated from the moment invariant.

#### ACKNOWLEDGMENT

A big thank to the Faculty of Computer Science of the Indonesian Muslim University who helped funding this research.

#### REFERENCES

- [1] T.K Das, A.K Tripathy, A.K Mishra, "Optical Character Recognition Using Artificial Neural Network," IEEE International Conference on Computer Communication and Informatics (ICCCI-2017). India 2017.
- [2] K.T. Islam, G. Mujtaba, R.G. Raj, H.F. Nweke, "Handwritten Digits Recognition With Artificial Neural Network," International Conference on Engineering Technology and Technopreneurship (ICE2T). IEEE. Kuala Lumpur, Malaysia. 2017.
- [3] F.A Fitters-Figueroa, C.M Travieso, M.K Dutta, A Singh, "Biometric Identifier Basic on Hand and Hand-Written Signature Contour Information," Proceeding of 2017 Tenth International Conference on Contemporary Computing (IC3). Noida, India. 2017.
- [4] M.O. Assayony and S.A. Mahmoud, "Integration of Gabor Features with Bag-of-Features Framework for Arabic Handwritten Word Recognition," 9<sup>th</sup> IEEE-GCC Conference and Exhibition (GCCCE). IEEE. 2017.
- [5] Y. Elarian, A. Zidouri, W. Al-Khatib, "Ground-truth and Metric for the Evaluation of Arabic Handwritten Character Segmentation," 14<sup>th</sup> International Conference on Frontiers in Handwriting Recognition. IEEE. 2014.
- [6] M.S. Nehra, N. Nain, M. Ahmed, "Benchmarking of Text Segmentation in Devnagari Handwritten Document," 7<sup>th</sup> Power India International Conference (PIICON). IEEE. 2016.
- [7] K. Tonmaithong, S. Annanab, N. Chotikakamthorn, "Handwriting Rearrangement for Thai Calligraphy," 8<sup>th</sup> International Conference on Information Technology and Electrical Engineering (ICITEE). IEEE. Yogyakarta, Indonesia. 2016.
- [8] R Pundlik, "Comparison of Sensitivity for Consumer Loan Data Using Gaussian Naïve Bayes (GNB) and Logistic Regression (LR)," 7<sup>th</sup> International Conference on Intelligent Systems. IEEE. 2016.
- [9] X Deng, J Guo, Y Chen, X Liu, "A Method For Detecting Document Orientation By Using Naïve Bayes Classifier," International Conference on Industrial Control and Electronics Engineering. IEEE. 2012.
- [10] A Fadil, I Riadi, S Aji, "A Novel DDoS Attack Detection Based on Gaussian Naïve Bayes," Bulletin of Electrical Engineering and Informatics, vol. 6, no. 2. pp. 140-148, 2017.