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Hand image reading approach method to Indonesian Language Signing System (SIBI) using neural network and multi layer perseptron

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ABSTRACT

Classification complexity is the main challenge in recognizing sign language through the use of computer vision to classify Indonesian Sign Language (SIBI) images automatically. It aims to facilitate communication between deaf or mute and non-deaf individuals, with the potential to increase social inclusion and accessibility for the disabled community. The comparison of algorithm performance in this research is between the neural network algorithm and multi-layer perceptron classification in letter recognition. This research uses two methods, namely a neural network and a multi-layer perceptron, to measure accuracy and precision in letter pattern recognition, which is expected to provide a foundation for the development of better sign language recognition technology in the future. The dataset used consists of 32,850 digital images of SIBI letters converted into alphabetic sign language parameters, which represent active signs. The developed system produces alphabet class labels and probabilities, which can be used as a reference for the development of more sophisticated sign language recognition models. In testing using the neural network method, good discrimination results were obtained with precision, recall and accuracy of around ±81%, while in testing using the multi-layer perceptron method around ±86%, showing the applicative potential of both methods in the context of sign language recognition. Testing of the two normalization methods was carried out four times with a comparison of the normalized data, which can provide further insight into the effectiveness and reliability of the normalization technique in improving the performance of sign language recognition systems.

1. Introduction

In recent years, neural networks have gained much attention due to their important role in various applications such as content-addressable memory, pattern recognition, and optimization. The process of learning or training an Artificial Neural Network (ANN) involves determining the weights in such a way that the network produces an output that matches the desired input. This often involves the minimization of an error function calculated based on the difference between the network output and the expected output from a set of training data. The Multilayer Perceptron (MLP) is the most commonly used model in neural network applications and uses a back propagation training algorithm [1]. The importance of architecture definition in MLP networks cannot be ignored, as a lack of connections can result in the network not being able to solve the problems it faces due to parameters that cannot be set sufficiently, while an excess of connections can result in overfitting of the training data [2]. Pattern recognition is a common problem that is currently gaining significant attention, whether in the context of facial recognition, fingerprinting, handwriting, or character pattern recognition from printouts. In general, pattern recognition techniques aim to classify and describe complex patterns or objects through measuring the properties or characteristics of these objects [3]. The stages involve preprocessing, feature extraction, and classification, which is often done by applying approximation methods, including ANN, in character pattern recognition systems [4], [5].

Neural networks are one of the artificial representations that attempt to simulate the learning process of the human brain [6]. The term "artificial" is used because this neural network is implemented through a computer program that is capable of carrying out various calculations during the learning process. Neural networks are used for modeling and learning to form a reference model. After learning, this network can be used for pattern matching, and neural network models can be classified based on various criteria, including learning methods [7]. In the context of architecture, input and output types can be binary or bipolar, depending on the need. Modeling with neural networks is an attempt to build intelligence and self-learning systems using simple components inspired by biological network models [8].

The goal of this research is to improve the ability of computer systems to effectively recognize letter patterns, even when provided with a limited number of examples. Although computer systems have weaknesses when faced with a large number of pattern examples, this research aims to find techniques that can improve the ability of computers to recognize and represent patterns [9]. One approach that has shown promising results is the use of artificial neural networks, which utilize image processing and neural network methods. Learning algorithms in neural networks, such as MLP, are a form of guided learning algorithm [10]. The neural network increases its weights at each iteration for each pair of input-output data (epoch), with the calculation of the error used as a parameter for weight improvement. This process stops when the error reaches a predetermined maximum limit [11]. The learning process is also affected by the learning rate [12]. MLP is one of the most commonly used network architectures in pattern recognition. MLP has a feed-forward structure involving input layers, hidden layers, output layers, and model parameters such as bias and adjustable weights [11]. This structure exhibits behavioral stability and fault tolerance and is capable of modeling functions with varying degrees of complexity, which depend on the number of layers and units in each layer [13]. The MLP training and testing process consists of prediction stages that are made by learning the training data. The MLP training and testing process is illustrated in Fig. 1. In terms of algorithms, the training process is carried out through a series of steps as follows.

Related research has examined the identification and recognition of each number character in printed SIBI with neural network methods [14], [15]. Other research applies the recognition of the most frequently used words to recognize the alphabet [16]. In addition, research has focused on optimization to combine neural network and MLP methods to optimize the data processing mechanism [11]. Also, there are studies that try to identify cardiac arrhythmia by using neural network and MLP simultaneously [13]. However, diverse writing styles have made handwriting identification an extensive and interesting research subject over the past decades. Therefore, the focus of this research is to compare various method approaches in recognizing hand patterns against language cues that have been converted into numerical data. Related research has been done to get 59.5% accuracy by identifying characters against hand patterns with Fourier transformed image extraction method [17]. The next research achieved an accuracy of 61% with the JST Backpropagation method [18]. Research using the same method on the classification of Hanacaraka Javanese script resulted in an accuracy of 74% [19]. However, until now there has been no research that specifically analyzes the comparison of neural network and MLP algorithms to classify SIBI images in the context of the alphabet. SIBI images are in the form of wrist images, which are basically simple and easy to classify. Therefore, it is necessary to analyze the performance comparison between neural network and MLPD by considering accuracy, precision, and root mean squared error. This research aims to provide a better understanding of the selection of suitable algorithms for classifying SIBI images. In this study, we trained the network with neural net algorithm together with multi-layer perceptron using Rapidminer 10.02 software. The input layer consists of 25 predictors, while the output layer has two units representing two categories in the dependent variable. Since the training samples were diverse, the hidden layer consisted of 18 to 26 hidden units. The test results using the neural network method showed accuracy, recall, and precision of about ±81%, while in the test with the multi-layer perceptron method it was about ±86%. The test was conducted four times by comparing the normalized data using both methods.

2. Method

In this study, the research process involved several stages, starting with data collection. The next stage involves data processing, specifically data normalization, which is then followed by testing the selected algorithm. The final stage is to test the method against the data, with the hope of producing a high level of accuracy and precision.

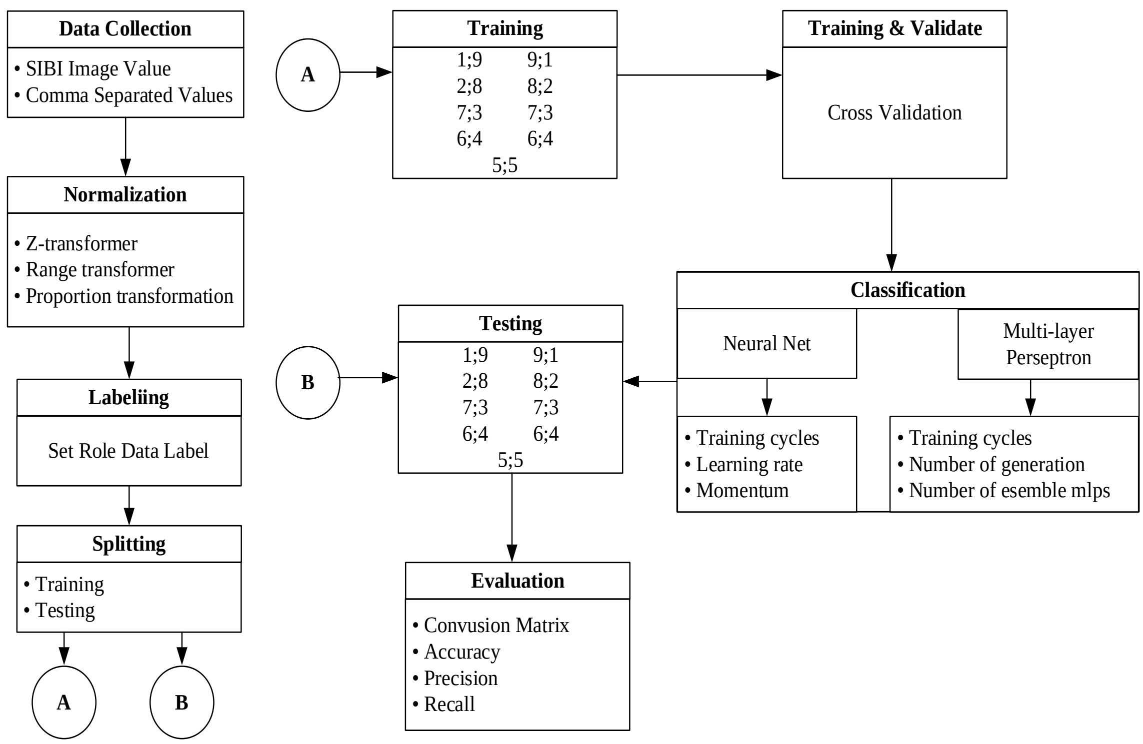

Fig. 1. Data Processing Flow

2.1. Data Collection

The type of data used in this research is the SIBI image conversion value, which is obtained from the image conversion source. Letter recognition for communication is very important today, especially for individuals with communication disorders. The goal of SIBI development is to facilitate sustainable communication for those with communication disorders. The conversion parameter values obtained were 25 alphabetic characters with a total of 32,850 data points.

2.2. Data Normalization

The process of scaling attribute values to fit a specified range is called normalization [20]. The data obtained from SIBI image conversion has a wide distribution, so normalization is necessary. The range of values categorized as legible letters have characteristic values to determine the similarity of the alphabet. Normalization ensures that diverse data attributes have the same influence when used for data analysis by making them uniform. Some of the normalization techniques used are:

- Min-Max Normalization is the process of rescaling data from one range to another [21]. This method uses the formula expressed in Equation (1) to transform the data to the target range.

$$X_{new} = \frac{X_{old}-X_{min}}{X_{max}-X_{min}} \quad (1)$$

- Z-Score normalization is done by removing the middle value of the data and then dividing it by the standard deviation [22]. The z-score normalization method is shown in formula (2).

$$X_{new} = X_{old} - \mu/\sigma \quad (2)$$

- Decimal Scale Normalization where this normalization method divides several previous result variables by the maximum result variable [23]. This approach is presented in Equation (3).

$$X_{new} = \frac{X_{old}}{X_{max}} \quad (3)$$

2.3. Classification

The classification algorithm used in this research is artificial neural network. The training program is a type of learning because the training method must be objective. It is called backward propagation because during training the error goes back to the base unit [24]. The network architecture used in this research is a multilayer network. The input layer, hidden layer, and output layer form a network [2]. The input layer consists of 16 neurons with derived feature values. The number of neurons in the hidden layer has been changed to improve performance [1].

- Neural Network

  This section presents details of the neural net and Multi-layer Perseptron methods to produce This section presents details of the neural net and Multi-layer Perseptron methods to produce accuracy and precision in measuring the accuracy level of hand shape reading in SIBI, the performance of the methods is measured alphabetically. MLP is the second classification algorithm used in this research as a comparison to the first method. MLP is part of supervised learning because the training method must be objective. It is called a perceptron because errors are fed back to the underlying unit during learning [12]. The network architecture used in this research is a multilayer network, which is a network architecture with many layers. The input layer, hidden layer, and output layer form a network. The input layer contains neurons that contain the extracted feature values. Change the number of neurons in the hidden layer for best results [22].

- Multi-Layer Perceptron

  The multilayer perceptron arises from the development of the basic perceptron, which consists of one or more hidden layers between the input and output layers. Here the neurons are arranged in layers that are connected continuously from the bottom layer to the top layer without any connection between different layers of neurons (see Fig. 2). The number of neurons in the input layer is equal to the number of measurements of the model problem, and the number of neurons in the output layer is equal to the number of classes. The selection of layers, the number of neurons per layer and their connections is called network design [25]. Architecture optimization is the key to a network that fits the parameters and scalability suitable for classification or regression. A multilayer perceptron is an ANN that consists of several layers, including one input layer, several hidden layers, and one output layer. Each MLP layer contains neurons that are all connected to neurons in the next layer. The input and output layers contain colored circle neurons, while the hidden layer has white circle neurons. The method used in this development is JST through multi-layer perceptron, a model with applications and training superior to simple JST formation [26]. The multi-layer perceptron method is a supervised learning approach in artificial neural network systems. When designing a neural network, the number of specifications that require identification must be considered a neural network consists of many neurons and inputs [27]. Multi-layer Perceptron is the simplest form of JST used to classify special patterns commonly called linearly separable, i.e. patterns that lie on opposite sides of a plane. Perceptron basically consists of a single neuron with synaptic weights and thresholds that can be set, Perceptron is limited to classifying only two classes, therefore the shortcomings of the perceptron method are improved into a multi-layer perceptron to reduce these problems [2]. Confusion matrix show as Table. 1.

Table 1. Confusion matrix

	Classification Results									
	K1	*K2*	*K3*	*K4*	*K5*	*K6*	*K7*	*K8*	*K9*	*...*	*K20*
K1	X										
K2		X									
K3			X								
K4				X							
K5					X						
K6						X					
K7							X				
K8								X			
K9									X		
...										X	
K20											X

2.4. Spliting

Separation of a dataset into two different subsets. The purpose of data division is to isolate a portion of the data for a specific purpose, such as model training, model testing. The result can see which accuracy and precision is better [13].

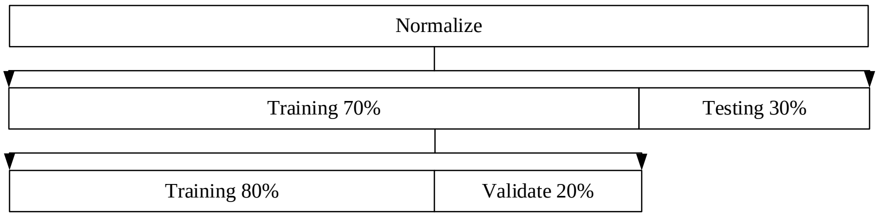

Fig. 2. Splitting Data

Data splitting is used for neural network and MLP algorithms, respectively, for training and testing [26]. Both algorithms use some of the total data for training and the rest for testing. Furthermore, the training dataset is divided into 70% for actual training and 30% for validation. Each alphabet in the alphabet dataset is used for training, testing, and validation procedures.

2.5. Testing

The data collected during the experiment is divided into two parts: training data and test data. In this experiment, we divided 32850 SIBI image transfer data by clustering the data into 20 groups. Cross validation is used as a data divider with a K value of 10, choosing the K value because it has a fairly high accuracy rate compared to K values above or below the specified value [20].

2.6. Evaluation

A performance measure approach in binary problem solving or confusion matrix is used to reassess neural network classification algorithms [28]. This evaluation approach is currently used to test two classes, but can be modified to handle multi-class classification. Fig. 3 shows the confusion matrix for obtaining accuracy and precision values [29], [30]. Equation (6) is used to obtain the accuracy value to determine the correctness of the data against the evaluation results.

$$Accuracy = \frac{\sum N_{correct}}{\sum N} \quad (4)$$

where ΣN correct is the number of correctly classified image data, and $\Sigma\ N$ is the number of available image data.

Precision is the ratio of positive correct predictions compared to the overall positive predicted results

$$Precision = \frac{TP}{(TP+FP)} \quad (5)$$

where n is the sample size, z is a constant 0.5 and p is the proportion of the prevalence of the event, d is the precision.

Recall is the ratio of positive correct predictions compared to all positive data. Recall answers the question of what percentage of the alphabet will be predicted compared to the entire actual alphabet

$$Recall = \frac{TP}{(TP+FN)} \quad (6)$$

3. Results and Discussion

Furthermore, the careful selection of parameters for the neural network approach, such as the training cycle, learning rate, and momentum, demonstrates a conscious effort to balance the model's potential for learning complicated patterns across the 200 training cycles. Similarly, the multi-layer perceptron parameters, which include a shorter training cycle of 10, 10 generations, and 4 ensembles, point to a more iterative and ensemble-based approach, potentially aimed at capturing multiple perspectives within the dataset. The interaction of these parameters emphasizes the complex tactics used to maximize each model's performance in the defined experimental contexts [31]–[34]. Specifications of Backpropagation as show in Table 2.

Table 2. Specifications of Backpropagation and MLP Artificial Neural Networks

Characteristic	Specification
MLP	
Training cycles	10
Number of generation	10
Number of esemble mlps	4
Neural Net	
Training cycles	200
Learning Rate	0.02
Momentum	0.8
Maximum Iteration	328
Testing	10/90; 20/80; 30/70; 40/60 ;50/50 ;40/60 ;30/70 ;20/80 ;10/90
Training	10/90; 20/80; 30/70; 40/60 ;50/50 ;40/60 ;30/70 ;20/80 ;10/90

3.1. Determination of the Number of K in K-Fold Cross-Validation

The data used in the experiment consists of 32850 sample trials of finger sensor readings consisting of alphabet reading objects A to Y. Testing is done by entering the type of .csv file in the method approval application, Rapidminer. Accuracy is the accuracy of alphabet selection based on sensor readings based on finger data performing actions [17]. Comparison of data values received by the sensor will detect all alphabets, then the sensor value that has a difference in value with the same alphabet, the accuracy value will be close to 100% [18]. Table 3 and table 4 show a level of accuracy, precision and recall of SIBI data reading based on two experimental methods used using Z-transformer normalization and Range Transformation. Fig. 3 is the Confusion matrix of MLP that has been trained and tested.

	true A	true B	true C	true D	true E	true F	true G	true H	true I	true K	true L	true M	true N	true O	true P	true Q	true R	true S	true T	true U	true V	true W	true X	true Y	class precision
pred. A	840	0	0	0	6	0	0	0	1	0	5	29	19	0	0	0	0	22	94	0	0	0	0	10	81.87%
pred. B	1	1097	2	11	2	122	7	10	5	47	9	0	3	15	0	0	12	5	0	32	5	49	3	0	76.34%
pred. C	0	5	930	59	2	1	147	4	1	3	6	0	1	63	1	2	2	4	4	1	0	1	14	1	74.28%
pred. D	3	1	14	711	1	2	47	0	7	3	29	7	2	87	0	0	3	2	0	1	0	0	26	1	75.08%
pred. E	12	1	0	8	672	0	8	0	10	0	1	18	2	14	0	1	0	34	3	0	0	0	0	4	85.28%
pred. F	0	30	26	0	8	1043	1	1	11	10	0	0	0	16	0	0	5	7	1	11	8	18	2	0	87.06%
pred. G	2	0	32	27	1	0	609	0	3	0	38	12	11	28	1	1	9	20	11	0	0	0	59	3	70.24%
pred. H	0	1	17	1	0	0	63	1120	1	2	1	1	21	3	19	8	4	0	0	2	2	0	7	0	87.98%
pred. I	9	8	10	30	55	17	19	0	915	21	24	48	29	27	0	1	5	98	53	1	0	0	15	95	61.82%
pred. K	0	0	0	3	0	1	3	10	0	588	0	0	7	0	0	0	1	1	0	24	25	1	0	0	88.55%
pred. L	43	0	2	0	0	1	19	0	1	19	1031	0	5	0	6	1	2	3	9	1	1	6	8	6	88.57%
pred. M	38	0	2	3	63	1	1	0	10	0	1	548	169	9	1	0	0	32	12	0	9	0	18	41	57.20%
pred. N	68	0	1	3	65	0	5	0	5	9	0	366	784	2	1	0	1	66	26	1	1	0	11	12	54.94%
pred. O	0	4	62	61	19	0	156	7	5	0	4	8	6	713	4	2	6	28	6	3	3	0	80	2	60.47%
pred. P	1	0	5	2	0	0	19	27	1	0	1	1	1	1	1462	113	0	5	5	0	1	0	2	5	88.50%
pred. Q	0	0	2	1	0	0	16	0	0	0	1	0	1	8	15	1204	0	5	0	0	0	0	0	0	96.09%
pred. R	1	10	0	39	4	6	8	5	6	154	2	9	10	8	0	0	1108	63	32	208	24	3	64	0	62.81%
pred. S	82	4	6	16	295	0	14	3	21	5	3	121	105	5	0	0	30	680	157	24	5	1	96	42	39.65%
pred. T	65	25	44	86	3	6	6	0	22	108	3	13	20	52	0	0	22	54	753	12	0	0	85	12	54.13%
pred. U	1	1	0	4	0	3	0	24	0	7	0	2	0	0	0	0	80	0	0	817	22	1	0	0	84.93%
pred. V	0	0	3	25	0	8	0	8	10	191	9	0	1	18	0	1	28	13	2	59	1156	50	3	1	72.89%
pred. W	0	8	10	12	0	7	8	0	3	23	6	0	0	12	0	4	2	0	0	12	9	1129	5	0	90.32%
pred. X	0	0	43	71	15	6	29	2	17	7	8	3	21	98	0	0	17	28	49	19	3	0	748	4	62.96%
pred. Y	16	0	0	39	0	1	1	0	47	0	5	0	2	1	0	0	0	3	0	0	0	0	1	1025	89.83%
class recall	71.07%	91.80%	76.80%	58.66%	55.49%	85.14%	51.35%	91.73%	83.03%	49.12%	86.86%	46.21%	64.26%	60.42%	96.82%	89.99%	82.87%	57.97%	61.87%	66.53%	90.74%	89.67%	59.98%	81.09%	

Fig. 3. Confusion Matrix MLP

Table 3 and Table 4 have been included to demonstrate the achieved levels of accuracy, precision, and recall in the context of SIBI data reading to provide granular insight into the performance metrics. These assessments were carried out utilizing two independent experimental methodologies, namely Z-transformer normalization and Range Transformation. Furthermore, Fig. 3 depicts a visual representation of the Multi-Layer Perceptron (MLP) model's Confusion matrix, highlighting its usefulness after both the training and testing periods. This thorough examination not only highlights the soundness of the experimental approach, but also provides light on the nuanced complexities of the acquired results.

Table 3. Best Normalization Z-Transformation Result

Scenario	Training Data	Test Data	Z-Transfromation					
			Accuracy (%)		*Precision (%)*		*Recall (%)*	
			Neural Net	*Automlp*	*Neural Net*	*Neural Net*	*Automlp*	*Neural Net*
1	50	50	77.81	83.17	78.39	83.37	77.39	82.86
2	60	40	79.94	85.17	80.19	85.42	79.54	84.93
3	70	30	78.99	81.55	79.20	81.96	78.56	81.21
4	80	20	81.02	84.02	**81.41**	84.23	80.63	83.71
5	90	10	**81.11**	**85.49**	81.32	**86.00**	**80.76**	**85.23**
6	10	90	67.46	73.35	67.00	74.66	67.01	72.90
7	20	80	74.45	79.17	75.11	79.91	73.94	78.80
8	30	70	76.49	81.00	76.59	81.42	76.08	80.70
9	40	60	77.99	83.03	78.54	83.63	77.58	82.78

Testing is done by dividing the data into test data and training data, the comparison means that the entire training data becomes training data and the rest becomes test data, before the training data enters the training data model, training is done with validate data [19]. The results of the combination at the feature level of the two methods can be seen in Table 3 and Table 4. The testing scenario will be tested based on the scenario by dividing the dataset into 50% training data and 50% testing data, so that the data to be tested for each class is three test data. Getting the results of the precision of the Neural Net method 77%, and MLP 82%, and for the precision of Neural Net 78% and MLP 82% and the recall value of neural network 80%.

Table 4. Best Normalization Range Transformation Result

Scenario	Training Data	Test Data	Range Transfromation					
			Accuracy (%)		*Precision (%)*		*Recall (%)*	
			Neural Net	*Automlp*	*Neural Net*	*Neural Net*	*Automlp*	*Neural Net*
1	50	50	77.81	82.77	78.39	83.21	77.39	82.47
2	60	40	79.94	84.47	80.19	84.86	79.54	84.20
3	70	30	78.99	81.38	79.20	81.84	78.56	81.00
4	80	20	81.02	84.08	**81.41**	84.34	80.63	83.78
5	90	10	**81.11**	**85.46**	81.32	**86.04**	**80.76**	**85.21**
6	10	90	67.46	73.78	67.00	74.71	67.01	73.31
7	20	80	74.45	80.40	75.11	81.11	73.94	80.10
8	30	70	76.49	80.53	76.59	80.91	76.08	80.16
9	40	60	77.99	83.52	78.54	83.80	77.58	83.2

Based on the results of testing the methods that have been carried out, neural networks have performance with a comparison of 80% training data and 20% test data getting the best accuracy of 82.30%, while MLP has an accuracy performance of 84.54%. The total computation time of the training and testing process in the neural network algorithm is much faster when compared to MLP. The precision for the neural network algorithm is 82.64%, while the MLP algorithm is greater than the neural network with a precision value of 84.79%.

3.2. Evaluation

In Fig. 3, it can be seen that the recognition of each letter for each test data has quite good results. Several times there were misrecognition of the letters A, C, E, G, M, N and S. The recognition error occurred because the features formed by each letter have a very high level of similarity. The letter Q cannot be recognized at all and is predicted to be the letter G. In contrast to letters such as letters B, D, F, I, L, V, W, X, and Y, the recognition of these letters is very good because they have features that have a low level of similarity compared to other letters. The letters J and Z which are dynamic can be recognized well because both letters are dynamic. Proven by Table 3 and Table 4 with a large level of precision, accuracy and recall, so that the results of the test scenarios that have been tested in Table 3 and Table 4 can produce an accuracy rate of 85.46% obtained from the Neural Net method.

4. Conclusion

Testing is necessary in this research to ascertain the characteristics of each letter, as the Indonesian Sign Language (SIBI) system contains several letters that have high similarities. After conducting extensive trials using neural network and multilayer perceptron (MLP) methods, it can be concluded that the static and dynamic features of SIBI can be recognized well, with an average accuracy of 81% using the neural network method and 85% using the MLP method. Under the best precision conditions with both methods and Range Transformation normalization, fingerprint reading on SIBI reached 86% accuracy using a training-testing ratio of 90:10. This model is developed to optimize the architecture of artificial neural network (ANN). Genetic algorithms are suitable for obtaining optimal solutions to nonlinear problems. This method was evaluated to determine the optimal number of hidden layers and connection weights in MLP, as well as the best weight matrix after training. We have proposed a new modeling approach for the MLP architecture optimization problem as a mixed integer problem with constraints.

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