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Backpropagation Neural Network Method For The Classification of Districts/Cities Based On Macro Socio-Economic Indicators In The Province Of South Sulawesi

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Abstract

Classification is a way of grouping objects based on the characteristics possessed by the objects of classified. One of the developing classification methods is the Backpropagation Neural Network. This study aims to look at the descriptive and classification results of the District/City Macro Socioeconomic Indicators in South Sulawesi Province. The data set comprises 24 observations with 9 variables, namely Population Density, Poverty Line, Gini Ratio, Open Unemployment Rate, Life Expectancy, Average Length of Schooling, Labor Force Participation Rate, Life Growth Rate, and GRDP at Current Prices. The results of the classification of districts/municipalities based on Macro Socioeconomic Indicators in South Sulawesi Province show that there are 2 groups of Macro Socioeconomic Indicators for Districts/Cities in South Sulawesi Province, namely group 1 and group 2. Group 1 is also known as a higher socioeconomic indicator compared to group 2. While group 2 is a lower socio-economic indicator compared to group 1. Based on the results of the classification of Macro Socioeconomic Indicators of Districts/Cities in South Sulawesi Province, the accuracy value is 70%, precision is 70%, recall is 100% and F1 score is 87%.

Keywords: Backpropagation Neural Network; Macro Socioeconomic Indicators; Classification

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1. Introduction

Based on Law No. 23 of 2006, residents are Indonesian citizens and foreigners residing in Indonesia. In sociology, a population is a group of people who occupy a certain geographical area and space. Socio-economic status is the position or position of a person in a community group, which is determined by the type of economic activity, education, and income. Socio-economic conditions have recently had a negative impact due to the COVID-19 pandemic. COVID-19 was first detected in China in 2019 and was first detected in Indonesia in March 2020. The COVID-19 pandemic in Indonesia has not only had an impact on public health but has also affected the economic conditions, education, and social life of the Indonesian people (Chairani, 2020).

Although South Sulawesi is one of the provinces with the highest economic growth in Indonesia. However, since the COVID-19 pandemic, economic stability in South Sulawesi has been disrupted. Production of goods declined in line with the slowdown in household consumption. A wave of layoffs (PHK) was inevitable until purchasing power decreased. It is estimated that around 1.2 million informal sector workers lost their jobs due to restrictions on activities related to COVID-19. Finally, economic growth is expected to decline drastically due to a decline in the performance of the production sector and the expenditure sector.

Based on the problems described, information on the classification of regencies/cities in South Sulawesi Province based on macroeconomic indicators is needed. One method that can be used to classify districts/cities in South Sulawesi Province based on macro-social economic indicators is by using the Artificial Neural Network method. Artificial Neural Network is one of the artificial representations of the human brain, which always tries to simulate the learning process in the human brain (Kusumadewi, 2010). Neural Networks are not programmed directly but are explicitly trained

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through learning algorithms to solve a given task, a process that leads to "learning" through experience. The advantage of a Neural Network is that the classifier process is nonparametric, so it can be used in all types of data and it will be better if more parameters are used and more data is used (Chiroma et al., 2019).

Backpropagation Neural Network or so-called backpropagation of artificial neural networks designed for operation on multilayer feedforward networks. There are three layers, namely input layer, hidden layer, and error layer. The learning process in Backpropagation Neural Network is carried out by adjusting the neural network weights in the backward direction based on the error value in a study (Cabreira et al., 2009).

2. Literature Review

2.1 Classification

Classification comes from the Latin word classis, which means grouping similar objects and separating dissimilar objects. In statistics, Classification is a way of grouping objects based on the characteristics possessed by the objects of classified. In the process, classification can be done in many ways, either manually or with the help of technology. Classification that is done manually is a classification that is done by humans without the help of intelligent computer algorithms. While the classification is done with the help of technology, it has several methods, including Naïve Bayes, Support Vector Machine, Decision Tree, Fuzzy, and ANN (Wibawa et al., 2018). In the classification, there are 2 processes carried out, namely the training and testing process. This process is carried out to determine the accuracy of the model built in the training process, generally using data called a test set to predict labels.

2.2 Backpropagation Neural Network

Backpropagation is one of the Artificial Neural Networks, which is a supervised learning method with a multi-layer network and has special characteristics of minimizing errors in the output generated by the network. Usually, in the Backpropagation Neural Network classification process, this Classifier works by carrying out two stages of calculation, namely forward calculation, which calculates the error value (error) between the system output value and the supposed value and backward calculation to correct the weight based on the error value.

Advance Phase (Feed Forward)

1) Each input unit (Xi, i=1,2,3,…,n) receives signal Xi and forwards the signal to all hidden layers.
2) Each layer of the unit (Zi, i=1,2,3,…,p) sums up the input signals as in equation (1)

$$Z_i n_j = V_0 j + \Sigma_{j=1}^{n} X_i V_{ij} (1)$$

Where:

$Z_i n_j$: unit output for Z_j

$V_0 j$: input layer weights are biased to hidden units to-j

X_i : unit input to-i

V_{ij} : the weight of the I layer input unit to the hidden layer j

Then apply the activation function to calculate the error signal as in Equation (2)

$$Z_j = f(Z_i n_j) \quad (2)$$

Where:

Z_j : the-j units in the hidden layer.

$Z_i n_j$: unit utput for Z_j

After that all signals are sent to Error.

3) Each unit error $Yk_i, K = (1,2,3, \dots, m)$ add up the error signal weights as in equation (3)

$$Y_i n_k = W_{0k} + \Sigma_{j=1}^{p} Z_j W_{jk} \quad (3)$$

Where:

$Y_i n_k$: net input for units Y_k

W_{0k} : hidden unit weights are biased to error units to-k

W_{jk} : the weight of the j hidden unit to the unit to-k

Z_j : value of the j hidden unit using the sigmoid activation function

Then calculate the activation function to calculate the error signal as in the equation (4)

$$Y_k = f(Y_i n_k)(4)$$

Where:

Y_k : the k unit in the output layer

$Y_i n_k$: net input for units Yi

Reverse Phase (Feed Backward)

1) Each input unit (Y_k, k = 1,2,3,…,m) will receive the pattern target related to the training input (training), then calculate the error as in the equation (5).

$$\delta_k = (t_k - y_k) f(Y_i n_k) \tag{5}$$

Where:

δ_k : output unit error value

y_k : value of the k unit of output using the function

t_k : error target value

$Y_i n_k$: net input unit Yi

f is the derivative of the activation function, then calculate the weight correction as in equation (6).

$$\Delta W_{jk} = \infty \delta_j Z_j \tag{6}$$

Where:

ΔW_{jk} : the change in the weight of the j hidden unit to the output to k

∞ : learning rate

δ_j : error value hidden layer

Z_j : the value of the j hidden unit with the sigmoid activation function

Then calculate the bias correction as in equation (7).

$$\Delta W_{0k} = (\infty)(\delta_k) \tag{7}$$

Where:

ΔW_{0k} : calculate the bias correction

∞ : learning rate

δ_k : error value output unit

Also sending δ_k to the unit on the rightmost layer.

2) Each hidden unit (Z_j, j = 1,2,3,…,p) adding up input deltas of the units in the middle layer as in equation (8).

$$\delta_i n_j = \Sigma_{k=1}^{m} \delta_k W_{jk} \tag{8}$$

Where:

$\delta_i n_j$: unit output for Z_j

δ_k : error value output unit

W_{jk} : hidden unit weight j to error *unit* k

Then calculate the error information by substituting this value with the activation function derivative as in equation (9).

$$\delta_j = \delta_i n_j f(Z_i n_j) \tag{9}$$

Where:

$\delta_i n_j$: unit output for Z_j

$Z_i n_j$: output from each unit Z_j

Then calculate the weight correction as in equation (10).

$$\Delta V_{jk} = (\infty)(\delta_j)(Xi) \tag{10}$$

Where:

∞ : learning rate

δ_j : error value hidden layer

X_i : input unit i

Then calculate the bias correction as in equation (11).

$$\Delta V_{jk} = \left(\infty\right)(\delta_j) \tag{11}$$

Where:

∞ : learning rate

δ_j : error value hidden layer

Weight Change Phase

1) After error unit (Y_k, k = 1,2,3,…,m) change the error and bias weight (Z_j, j = 1,2,3,…,p) as in equation (12)

$$W_{jk}(new) = W_{jk}(long) + \Delta W_{jk} \tag{12}$$

Where:

W_{jk} : hidden layer weight j to error unit k

Each hidden unit (Z_j, j = 1,2,3,…,p) change weight and bias input (Z_i, i = 1,2,3,…,p) as in equation (13).

$$V_{ij}(new) = V_{ij}(old) + \Delta V_{ij} \tag{13}$$

Where:

V_{ij} : connection weight value from unit Xi to unit Yk

2) This stop condition is fulfilled if the resulting error value is less than the reference error value or the training has reached the specified epoch (Syahputra & Harjoko, 2011).

2.3 Training and Testing

Training and testing is a process used to define models or functions that differentiate concepts or data classes and can also be used to predict classes that are not available in objects. The training data is used for the training set whose labels are known to build the model while the data testing is used to determine the accuracy of the model that has been built during the training process. In the testing process, data is generally called a testing set to predict labels, where the testing set and training set are different data.

2.4 K-Means

K-Means clustering is an unsupervised learning algorithm that is used to group unlabeled datasets into different clusters. The K symbol in K-means clustering indicates the number of clusters used. Cluster refers to a collection of data points that are gathered together due to certain similarities. The purpose of the K-Means clustering process is to minimize the objective function that has been set in the clustering process. This goal is carried out by minimizing the variation in the data in the cluster and maximizing the variation in the data in the other clusters.

2.5 Social

Humans are social beings because their lives are always related to other communities. This social nature is an implication of the interaction relationship with the environment with various backgrounds. Social science is also the science of the behavior of people's lives as social beings. In simple terms, social is a place or place for association of life between humans whose manifestation is in the form of human groups or organizations, namely individuals or humans who interact or relate reciprocally, not humans in the physical sense. In showing their status, a person uses a status symbol to differentiate them from other people in society (Nurjannah, 2014).

2.6 Economy

Economy is a field of study concerning the management of individual, community and state material resources to improve the welfare of human life. Because economics is the science of human behavior and actions in which to fulfill their varied and developing life needs with existing resources through choices of production, consumption and or distribution activities (Rahmadhani, 2015).

2.7 Macro Indicator

General indicators (macro) are composite indicators of various economic and social development activities. The macro development indicators consist of economic growth, inflation, per capita income, and a decrease in the number of unemployed. Economic growth is the main indicator which is very important to ensure the continuity of development to move the wheels of development. Without economic growth, development program activities will experience stagnation which will lead to an increase in the number of unemployed and an increase in the number of poverty.

3. Research Method and Materials

Based on existing data, this study uses a quantitative approach. Quantitative research methods are ways to gain knowledge or solve problems carefully and systematically, and the data collected is in the form of a series or collection of numbers (Nasehudin & Gozali, 2012). The type of data used in this study is secondary data obtained from the BPS of South Sulawesi Province through the publication of South Sulawesi in Macro Social Economic Indicators of South Sulawesi Province.

4. Results and Discussion

Descriptive analysis aims to describe a data briefly and can provide core information so that the raw data is easier to understand and more meaningful. This study uses data on district/city socio-economic macro indicators in South Sulawesi Province in 2021. The characteristics of the data are explained in a descriptive form for each variable which is presented in Table 1.

Table 1. Descriptive Analysis of Socioeconomic Macro Indicators

No	Variable	Minimum value	Maximum value	Median	Mean
1	Population Density	43	7161	212.5	603.6
2	Line Of Poverty	341484	475444	365719	373436
3	Gini Ratio	0.332	0.406	0.364	0.368
4	Open Unemployment Rate	2.34	13.18	4.11	4.75
5	Life Expectancy	66.49	73.41	69.79	69.58
6	Average Lenght Of School	6.60	11.43	7.97	8.27
7	Labor Force Participation Rate	57.78	77.99	65.56	65.83
8	Economic Growth Rate	-1.39	8.86	5.12	4.90
9	PDRB At Current Prices	6836	190318	13418	22728

After conducting a descriptive analysis on the Macro Socioeconomic Indicator data, the next step is inputting the data then standardizing the data. Data standardization is carried out to standardize data whose format is not consistent using a certain format, so that all data becomes standard. The results of the standardization of the Macro Socioeconomic Indicator variables can be seen in Table 2.

Table 2. Standardization of Socioeconomic Macro Indicator Variables

	X_1	X_2	X_3	...	X_9
1	-0.35030782	1.10873763	-0.809203160	...	-0.4354163
2	-0.18199245	-0.14698052	-0.352241375	...	-0.1882097
3	-0.07234302	-0.33612077	-2.065848	...	-0.3465933
⋮	⋮	⋮	⋮	...	⋮
24	0.09527395	0.31871077	-0.580722	...	-0.384001

Before classifying, the first thing to do is clustering. The method used is K-Means which is a non-hierarchical method. In the non-hierarchical method, the first thing to do is to determine the number of clusters at the beginning of the study because determining the number of clusters greatly influences the grouping results that will be produced. The method to be used in determining the number of clusters is by using the silhouette coefficient. The results of determining the number of clusters using the silhouette coefficient can be seen in Figure 1.

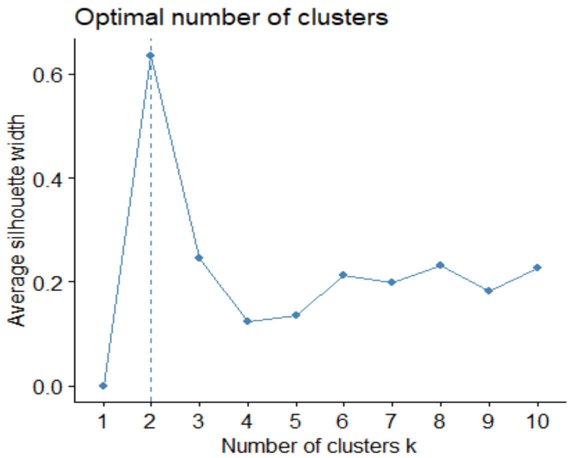

Figure 1. The Results of Determining the Number of Clusters

Based on Figure 1, which has the highest peak, namely number 2. So that the number of clusters to be used is 2 clusters/group. Clustering is a technique that functions to map data to certain groups or clusters. Each data is grouped based on its similarity with other data. Data that has the same characteristics will be included in the same cluster and data that has different characteristics will be placed in another cluster. The clustering method that will be used in this study is the K Means method. K-Means is a non-hierarchical clustering method that has a relatively fast computation time. By determining the number of clusters using the silhouette coefficient so that 2 groups are formed. In group 1 there are 19 group members, while in group 2 there are 5 group members. The results of the grouping of Macro Socioeconomic Indicators can be seen in Figure 2.

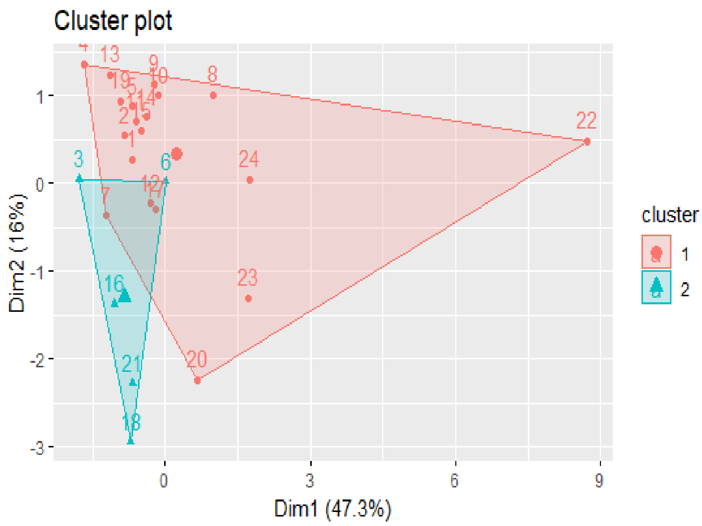

Figure 2. Grouping of Macro Socioeconomic Indicators

After grouping using the K-Means method, then look at the final centroid value of the Macro Socioeconomic Indicator. The following is the final centroid table after grouping.

Based on Table 3, each final centroid is obtained from all variables in the 2 groups. For Regencies/Cities especially in Population Density (X_1), Poverty Line (X_2), Gini Ratio (X_3), Open Unemployment Rate (X_4), Average Years of Schooling (X_6), and GRDP Based on Current Prices (X_9) which those in group 1 have a higher final centroid value than group 2. Whereas for Regencies/Cities especially in Life Expectancy (X_5), Labor Force Participation Rate (X_7) and Economic Growth Rate (X_8 which are in group 1 have centroid values lower end than group 2.

Table 3. Final Centroid Value

	Group	
	1	2
X_1	689	280
X_2	375774	364551
X_3	0.370	0.360
X_4	5.13	3.28
X_5	69	71.8
X_6	8.31	8.13
X_7	63.9	73.1
X_8	4.52	6.34
X_9	25561	12049

In classification, there are several steps, one of which is testing the data partition. This test aims to find out which data partition is the best. Before doing modeling, partitioning is done 4 times by dividing the data into two, namely training data and testing data. The first is dividing the data by 50% training data and 50% testing data, the second is dividing data by 60% training data and 40% testing data, the third is dividing data by 70% training data and 30% testing data, the fourth is dividing data by 80% training data and 20% testing data, and the fifth is dividing data by 90% training data and 10% testing data. After dividing the data into training data and testing data, the next step is to test the results of dividing training data and testing data using the confusion matrix as a reference. The confusion matrix represents predictions and actual (actual) conditions from the data generated by the backpropagation neural network method. Based on the results of the confusion matrix, we can determine accuracy, precision, recall, and f1 score.

Table 4. Confusion Matrix

	Actual	
Predict	TP	FP
	FN	TN

where:

TP : True Positive
FP : False Positive
TN : True Negative
FN : False Negative

After testing the data partition using the confusion matrix, the values for accuracy, precision, recall, and f1 score are obtained as follows.

Table 5. Data Partition Test Results

Training	Testing	Accuracy	Precision	Recall	F1 score
50%	50%	0.75	0.75	1	0.86
60%	**40%**	**0.86**	**0.86**	**1**	**0.92**
70%	30%	0.82	0.82	1	0.90
80%	20%	0.79	0.79	1	0.88
90%	10%	0.77	0.77	1	0.87

Based on Table 5, it can be seen that the partition test on data with a partition of 60% training data and 40% testing data gets an F1 score of 92%. The following is a graph of the results of the data partition as a whole.

Before calculating the accuracy of the backpropagation neural network mode, it is also necessary to determine the number of hidden layers and the learning rate value. The determination of the number of hidden layers and the value of the learning rate is carried out by trial and error because there are no definite rules regarding the number of hidden layers and the value of the learning rate. Determination of the number of hidden layers and the value of the learning rate is used if the error value is lower. Based on the results of determining the error value, the best number of hidden layers is 9 with the best learning rate value of 0.002 because it has the smallest error value of 1.010727. Based on the results of the analysis that was carried out before which the best distribution of training data and testing data was obtained, namely 60% training data and 40% testing data to the number of hidden layers, namely 9 and the best learning rate value, namely 0.002, so as to obtain an accuracy of 70%. The network structure in the backpropagation neural network can be seen in Figure 4.

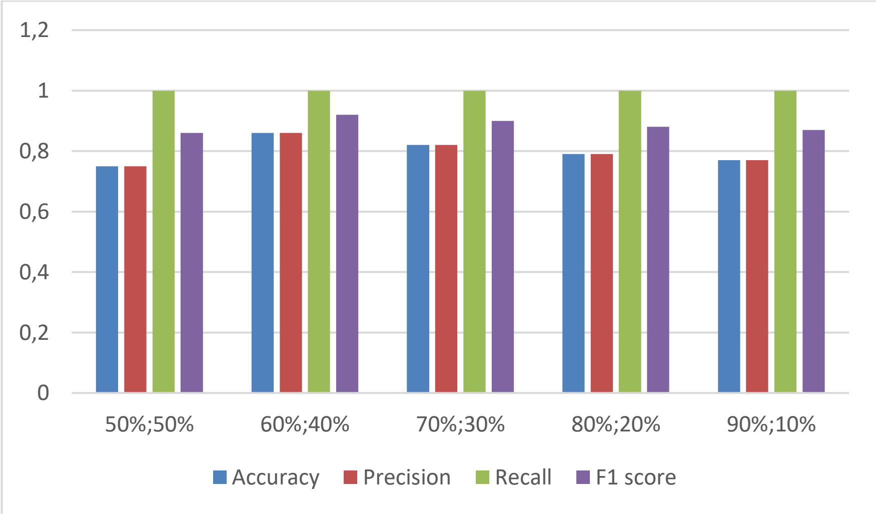

Figure 3. Data Partition Test Chart

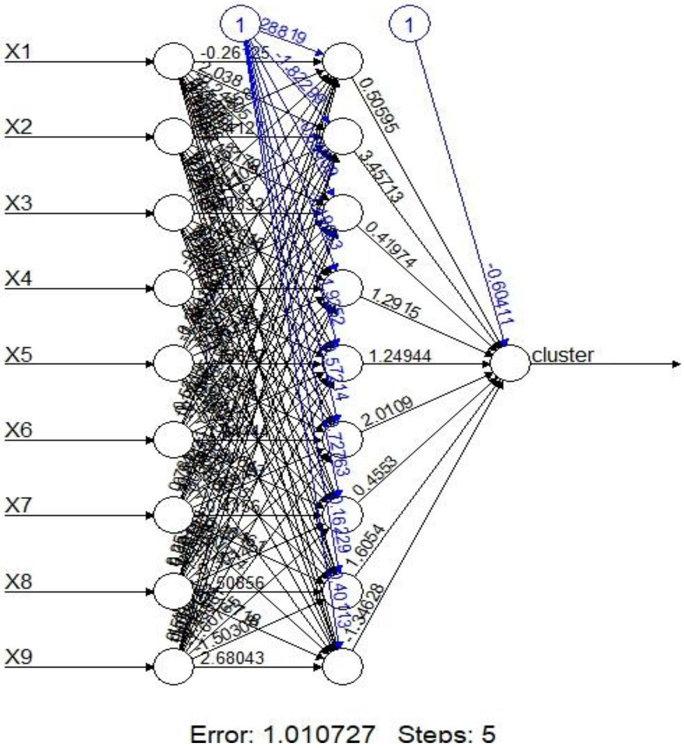

Figure 4. Backpropagation Neural Network Structure

5. Conclusions

Based on the results of the testing and research that has been done, the researcher can draw the conclusions:

a. The average population density of districts/cities in South Sulawesi province is 603.6 people/Km^2. The average district/city poverty line in South Sulawesi Province is 373,436. The average Gini Ratio for Regencies/Cities in South Sulawesi Province is 0.368. The average district/city open unemployment rate in South Sulawesi province is 4.75%. The average life expectancy of districts/cities in Sulawesi Province is 69.58%. The average length of district/city schooling in South Sulawesi Province is 8.27 years. The average District/City Work Force Participation Rate in South Sulawesi Province is 65.83%. The average economic growth rate for districts/cities in

South Sulawesi province is 4.90%. The average GRDP on the basis of valid prices for districts/cities in South Sulawesi province is 22,728.

b. In classifying Macro Socioeconomic Indicators using the Backpropagation Neural Network, grouping was first carried out with the results of the grouping forming 2 groups, in group 1 there were 19 group members, while in group 2 there were 5 group members. The results of the classification of districts/municipalities based on Macro Socioeconomic Indicators in South Sulawesi Province show that there are 2 groups of Macro Socioeconomic Indicators for Districts/Cities in South Sulawesi Province, namely group 1 and group 2. Group 1 is also known as a higher socioeconomic indicator compared to group 2. While group 2 is a lower socio-economic indicator compared to group 1. Based on the results of the classification of Macro Socioeconomic Indicators of Districts/Cities in South Sulawesi Province, the accuracy value is 70%, precision is 70%, recall is 100% and F1 score is 87%.

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