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Optimization artificial neural network classification analysis model diagnosis Gingivitis disease

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ABSTRACT

Gingivitis is a disease that can be caused by the buildup of bacteria and plaque caused by leftover food. This disease can attack anyone, especially children who are not aware of maintaining dental and oral health. This study aims to build and optimize the classification analysis model for the diagnosis of Gingivitis. The classification analysis model was built using the artificial neural network (ANN) method which was optimized using fuzzy logic and the multiple linear regression (MRL) method. Optimization with fuzzy aims to develop a pattern of rules in the detection. The MRL method is also used as a process of measuring analysis patterns to ensure the analytical model presents maximum results. The results study indicate that the optimization of fuzzy and MRL methods provides excellent output. These results are based on the fuzzy output which can provide a pattern of 40 rules. The MRL method is can present the level of correlation of each analysis variable with a significant output having an average value of 94.2%. Based on the results of this study, the analysis model that is optimized with the fuzzy logic method and MRL contributes to maximizing the process of diagnosing Gingivitis.

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1. INTRODUCTION

Health is a basic human need and also a supporting factor in carrying out activities [1]. One of the health that needs to be considered is dental and oral health [2]. Oral and dental health is a difficult thing to pay attention to for the community, especially among children [3]. This will later lead to the development of disease due to a minimal of attention to hygiene and oral and dental health [4].

One of the disease of the mouth and teeth is Gingivitis [5]. This disease is a disease that is felt in the gums with painful conditions and is characterized by swelling around the base of the tooth [6]. This disease condition can originate from the accumulation of food on the teeth and gums [7]. The pile of food residue will cause changes in a hardened form which can be referred to as dental plaque [8]. Previous studies reported that basic hygiene causes this disease due to a minimal of knowledge [9].

Based on this, we need a system that can be adopted properly in providing knowledge to the public about oral and dental health [10]. Furthermore, the system built can make it easier so that it can be used as an alternative solution [11]. Other studies explain that the system built can be effective and efficient in recognizing, understanding, and preventing dental and oral disease [12]. The same research also explains that the system design can be used as an initial treatment for the community and can be used as education for knowledge about this disease [13].

One of the implementations in handling these problems can be seen in a classification analysis model [14]. The classification analysis model can produce outputs by grouping disease on the weighted values obtained, that is severe symptoms of 0.693144314, moderate symptoms of 0.222716022, and symptoms of 0.084139664 [15]. Other classification analysis models also showed significant results with an accuracy rate of 75.5% and a mean square error of 0.05348436995 [16].

Based on previous research, it can be seen that the analytical model is still not optimal in conducting the classification process for Gingivitis desease. It can be seen that the proposed model still requires optimization to produce maximum results. The analysis of the model to be built adopts the artificial neural network (ANN) pattern model. ANN is a method used in the classification analysis process, presenting a fairly good output [17]. ANN conducts learning in analysis to provide optimal output results [18]. The performance of ANN can carry out the analysis process in classifying or predicting presenting fairly good results [19].

The ANN learning algorithm that can be used to perform classification analysis is the backpropagation algorithm [20]. The algorithm can solve complex problems by mathematically calculating the weighting of the network [21]. Backpropagation is an algorithm developed in a machine learning concept by adopting supervised learning [22]. Research in the process of analyzing this disease classification results in optimal machine learning performance and presents new knowledge in a pattern for detecting Gingivitis disease [23]. The same study also reported that ANN with backpropagation algorithm in deep learning concept provides effective performance in the detection of Gingivitis disease [24]. Followed by research adopting the application of backpropagation combined with the grey level co-occurrence matrix (GLCM) method presents a good performance in reading Gingivitis disease [25].

ANN performance can be developed optimally by using fuzzy logic which presents the best analytical model [26]. The combination of fuzzy logic with ANN is the most effective for analysis compared to other empirical models based on input parameters for better result efficiency [27]. Fuzzy logic can show a better ANN performance improvement based on the parameter values used [28]. Not only fuzzy logic can be adopted, but the ANN analysis method is also able to measure the effectiveness of ANN performance [29]. Multiple linear regression MRL performance can see the relationship of the patterns formed to be used in the implementation of model analysis in the case of prediction and classification [30]. MRL adopts the concept of calculation in measuring the performance of the ANN analysis model [31].

Based on this explanation, this study will later carry out the process of diagnosing Gingivitis. The diagnostic process is presented in a neural network classification pattern model that is built. The pattern analysis model will be optimized using fuzzy logic to generate diagnostic rules. The pattern analysis model that was built will also be measured using the MRL method to see the existing relationship between variables and network output. This optimization process will be updated to produce an optimal analysis pattern model in the diagnosis process. The analysis of this model will later become the basis for relevant parties in making decisions for the clinical diagnosis process. Overall, this research can be useful to help related to providing education about dental and oral disease and to the public about the management of Gingivitis.

2. METHOD

The classification analysis process in the diagnosis of Gingivitis is built using several stages. These stages are presented in the form of a research framework to produce optimal analysis outputs. The process stage begins with analyzing research datasets to determine initial knowledge about the symptoms and types of Gingivitis. The analysis process aims to determine the variables that will be used in the diagnosis process. After the analysis stage is carried out, the process is continued by testing fuzzy logic to find patterns of classification rules. The result rule pattern will be an analytical model that will be built using ANN. The pattern is built in an analytical model that can be described in the network architecture. After the pattern model is formed, the process continues with learning by adopting a training process and network testing. The results of network learning will later be measured based on the model using the MRL method to ensure whether the model presents the best analytical model. The results of the MRL measurement have a performance that can present the level of accuracy of the classification analysis pattern. The form of the research framework can be seen in Figure 1.

Figure 1 describes the stages of the work process which is presented in the form of a classification analysis in a research framework. The framework model was developed using the ANN method which was optimized with fuzzy logic and the MRL method. The classification analysis model developed presents a structured analysis process flow for diagnosing Gingivitis. The outputs obtained are expected to provide precise and accurate diagnostic results in determining the type of Gingivitis disease.

2.1. Fuzzy logic

Fuzzy logic is a logic that was developed in determining a value that has a level of uncertainty in data [32]. Fuzzy logic is also a type of logic that has multiple and interconnected values [33]. Fuzzy logic uncertainty can be interpreted as a process used to classify a value [34]. Some things need to be considered in fuzzy logic,

namely fuzzy sets and the rules that are formed [35]. The stages of the process carried out on fuzzy logic can be seen in Figure 2 [36].

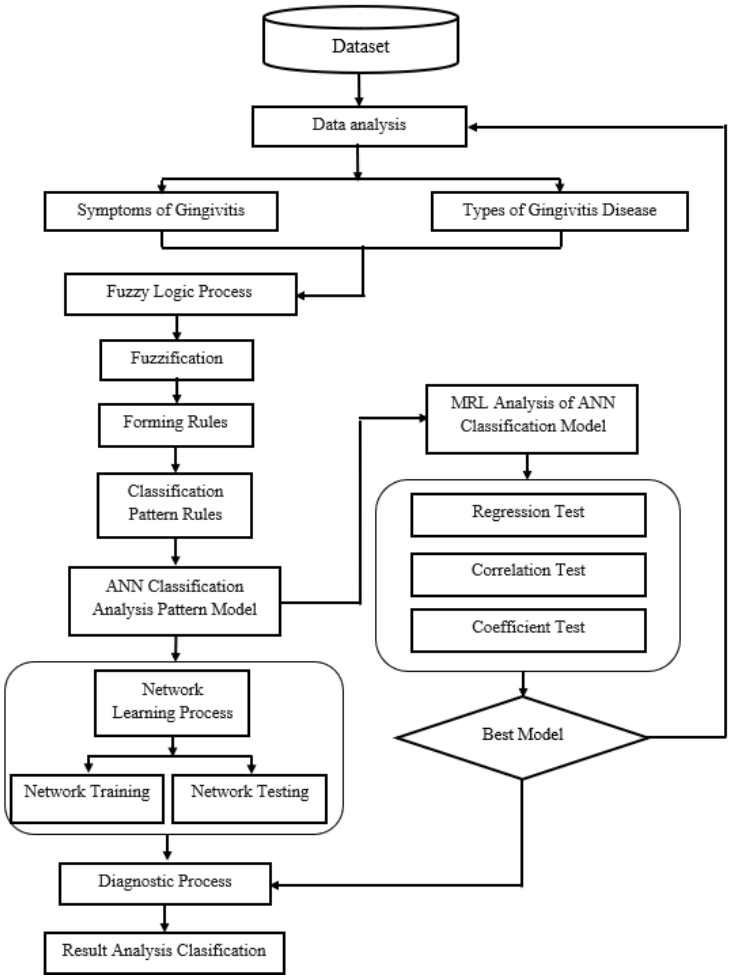

Figure 1. Research framework

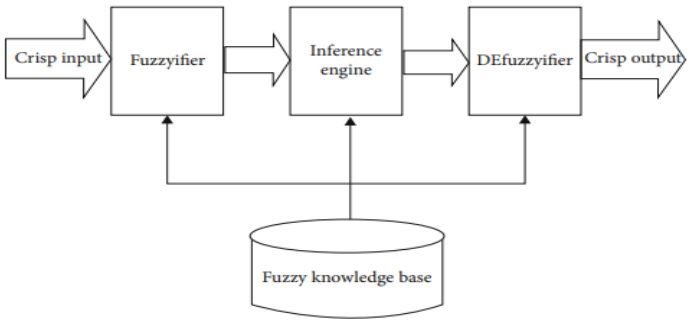

Figure 2. Stages of the fuzzy logic process

Figure 2 is the stages of the fuzzy logic process. The stages begin with providing input and then the fuzzification process. The fuzzification process aims to transform data by entering a weighted value so that later the data can be processed in the inference engine stage. The inference engine stage aims to find a pattern of rules formed based on the parameters and previous weighting. The result of the formed rule pattern will be

defuzzification to see the output of the analysis process. The output obtained will be new knowledge presented in the form of basic rules [36].

2.2. Artificial neural network

ANN is a technique or a method developed by adopting a neural network to carry out the analysis process [37]. ANN is able to present effective outputs to deal with certain problems [38], [39]. The concept of ANN is able to carry out the learning process based on a model that is built with mathematical calculations [40]. The learning is applied in a step that is presented in the algorithm based on the network architecture [41], [42]. In more detail, the concept of ANN can produce outputs to be taken into consideration in decision making [43].

2.3. Multiple linear regression

MRL is one of the statistical methods used to measure the performance of a model based on predictor variables [44]. MRL has independent and dependent variables in a model or pattern and is used to measure the relationship and relationships that occur in it. The MRL mathematical equation can be seen in (1) [45].

$$Yi = \beta 0 + \beta 1xi1 + \beta 2\ xi\ 2 + \beta 3xi\ 3 ..... \beta pxip \quad (1)$$

In (1) explains that the mathematical calculation process in the MRL analysis tests the independent variables. In this equation, the value of is a constant value which will later form a regression model. The regression model will also form a relationship that is formed based on the output of the correlation analysis process [45]. The equation used in the correlation analysis can be seen in (2) [46].

$$R = \frac{n\sum xy - (\sum x)(\sum y)}{\sqrt{n(\sum x^2(\sum x^2) - \sqrt{n(\sum y^2(\sum y^2)}} \quad (2)$$

In (2) explains that the R-value obtained is based on the overall calculation between the predictor variable value and the output. The forestry results in the level of relationship of all indicators with the results of the analysis obtained previously [46]. Based on these equations, the MRL analysis process can measure the performance of the analysis pattern in diagnosing Gingivitis.

3. RESULTS AND DISCUSSION

The process of discussing this research begins with the analysis stage of the research dataset. Stages of analysis is done by analyzing the type of disease and symptoms of Gingivitis. The results of the analysis stages can be presented in Table 1.

Table 1. Analysis of Gingivitis disease classification and symptoms

Code	Types of disease	Symptom code	Symptom description
P01	Undiagnosed	G01	Teeth often bleed when teeth
		G02	Blackish red gum color
P02	Acute	G03	Bad breath often
		G04	Frequent pain when chewing food
P03	Chronic	G05	Gums shrink so that the roots of the teeth are visible
		G06	Gums often swell and hurt

Table 1 shows the initial knowledge in the process of diagnosing the type of Gingivitis disease classification. Types of diagnosis classification are divided into three namely Chronic Gingivitis, Acute Gingivitis and Undiagnosed. After the analysis process, it is continued to perform analysis using fuzzy logic. The process of fuzzy logic analysis begins with fuzzyfication to provide initialization of the weighting of the results of the previous analysis process. After the fuzzyfication process, the analysis process is entered into the inference engine process. The results of the inference engine process produce classification pattern rules. These results show that fuzzy logic produces 40 rules of classification analysis patterns for the diagnosis of Gingivitis. The results of the rules generated by fuzzy logic can be seen in Table 2.

Table 2 is the result of the analysis using fuzzy logic. The results are presented in the form of pattern rules that will be used in building a classification analysis pattern with ANN. The ANN analysis process will be carried out by designing a network architecture model about the network input parameters based on the knowledge that has been obtained previously. The network architecture model can be seen in Figure 3.

Table 2. Rules of fuzzy logic process analysis pattern

RULE	G01	G02	G03	G04	G05	G06	P01
R001	Yes	Yes	Yes	Yes	Yes	Yes	Chronic
R002	Yes	Yes	Yes	Yes	Yes	Possible	Chronic
R003	Yes	Yes	Yes	Yes	Yes	No	Acute
R004	Yes	Yes	Yes	Yes	Possible	Yes	Chronic
R005	Yes	Yes	Yes	Yes	Possible	Possible	Acute
….....	….....	….....	….....	….....	….....	….....	….....
….....	….....	….....	….....	….....	….....	….....	….....
R36	No	No	No	No	Yes	Yes	Undiagnosed
R37	No	No	No	Yes	Yes	Possible	Undiagnosed
R38	No	No	No	Yes	Yes	No	Undiagnosed
R39	No	No	No	Yes	Possible	Yes	Undiagnosed
R40	No	No	No	Yes	Possible	Possible	Undiagnosed

Figure 3 explains that the ANN analysis model was built by adopting the input layer, hidden layer and output layer. After the formation of the ANN analysis model, the learning process is carried out using the backpropagation algorithm. The learning process includes training and testing of network patterns that have been formed. The results of network learning can be presented in Table 3.

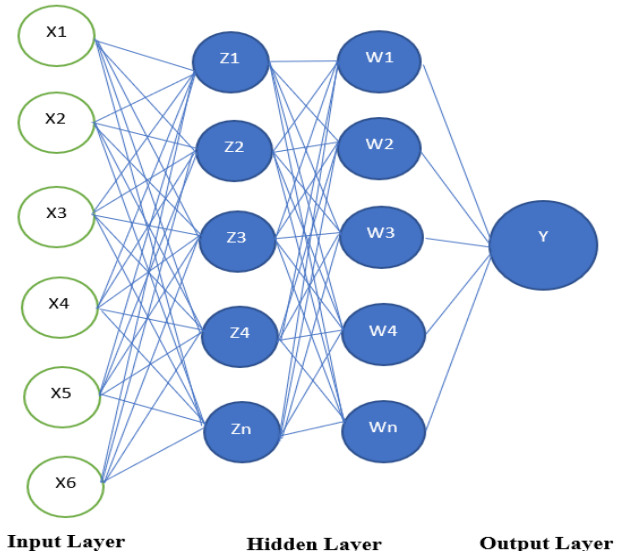

Figure 3. ANN analysis model architecture

Table 3. Learning outcomes of ANN

Architecture	Training			Testing		
	Accuracy	MSE	Performance	Accuracy	MSE	Performance
Single hidden layer						
(6-5-1)	99,984200	0,015800	0,000158	99,991900	0,008100	0,003900
(6-10-1)	99,842600	0,157400	0,001000	99,842600	0,157400	0,005200
(6-15-1)	99,649600	0,350400	0,003504	99,968000	0,032000	0,003300
(6-20-1)	99,909900	0,090100	0,001000	99,909900	0,090100	0,007200
(6-25-1)	99,975100	0,024900	0,001000	99,975100	0,024900	0,003700
Multi hidden layer						
(6-5-5-1)	99,905200	0,094800	0,001600	99,908700	0,091300	0,001600
(6-10-5-1)	99,992500	0,007500	0,000845	99,992500	0,007500	0,000845
(6-10-10-1)	99,990000	0,010000	0,006300	99,983100	0,016900	0,003800
(6-15-10-1)	99,870900	0,129100	0,001400	99,998100	0,001900	0,001400
(6-15-15-1)	99,957000	0,043000	0,008600	99,957000	0,043000	0,004100

Table 3 presents the learning outcomes of the ANN analysis model in classifying the diagnosis of Gingivitis. The learning results show that the network pattern with the 6-20-1 architectural model is the best

model. The ANN analysis model will later be processed to measure the significance pattern of the analysis output using MRL. The process of measuring the pattern of analysis will measure the level of regression, correlation, and coefficient. The results of the MRL analysis stages can be seen in Tables 4-6.

Table 4. Multiple linear regression results

Model Summary									
					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the	R Square	F Change	df1	df2	Sig. F
1	.942[a]	0,963	-0,033	2,47352	0,293	0,899	6	13	0,942

a. Predictors: (Constant), X6, X3, X4, X1, X2, X5

Table 5. Test coefecient and correlation result

Coefficient Correlations[a]								
Model			X6	X3	X4	X1	X2	X5
1	Correlations	X6	1,000	0,768	0,617	0,708	0,814	0,622
		X3	0,768	1,000	0,567	0,661	0,717	0,540
		X4	0,617	0,567	1,000	0,568	0,776	0,765
		X1	0,708	0,661	0,568	1,000	0,811	0,604
		X2	0,814	0,717	0,776	0,811	1,000	0,669
		X5	0,622	0,540	0,765	0,604	0,669	1,000

a. Dependent Variable: Y

Table 6. Analysis of variance result

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	33,012	6	5,502	0,899	.942[b]
	Residual	79,538	13	6,118		
	Total	112,550	19			

a. Dependent Variable: Y

b. Predictors: (Constant), X6, X3, X4, X1, X2, X5

Results based on the MRL analysis process, Table 4 presents a significant result of 94.2%. These results prove that the relationship variable with the output has a relationship in the diagnosis process. The results of the MRL analysis also have a standard error value of 2.47%. Table 5 also presents the measurement of the correlation and the level of the coefficient of each variable with the output. The correlation and coefficient measurements obtained show that each variable has a fairly good correlation level with a value above 55%. Based on Table 6, it can be seen that the overall results of the MRL analysis are presented in the ANOVA table which describes that the measurement process of the classification analysis pattern model provides optimal results. Overall, the analysis model that has been built has been well tested by presenting the maximum output.

Based on the discussion carried out in this study, the diagnosis process by adopting a classification analysis model gives very good results. The analysis of the classification model that was built was able to work better than the analysis of the previous model. Fuzzy logic and MRL can play an active role in developing model analysis in ANN so that the output given has a fairly high level of accuracy. Overall, the analysis process presented provides an update for the development of a classification analysis model for the diagnosis of Gingivitis. The results of this study can later be used as a reference in decision making and help to be used as an alternative solution in educating the public about Gingivitis.

4. CONCLUSION

The process of diagnosing the disease using the ANN classification analysis model gives a fairly good output. The result of the analysis shows that fuzzy logic has an important role in forming the pattern of diagnostic rules. MRL performance provides sufficient results in describing the relationship between data analysis patterns with an accuracy rate of 94.2%. The results of this study indicate that the ANN analysis model optimized with fuzzy logic and the MRL method have a fairly effective and effective performance in dealing with problems in diagnosing Gingivitis. Overall, the results of this study make a major contribution to the development of an analytical model for solving a problem.

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