Comparing Decision Tree and Artificial Neural Network Model in Predicting Bank Approval on Customer Credit

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Abstract

Banks have various services offered to their customers, one of which is credit. Credit is a service that provides loans to customers with payment terms and agreements. In the process, these services often experience problems in terms of the repayment process. So, this study aims to look at customer profile data and classify it into two groups, namely customers who have and do not have the opportunity to apply for the loans. This process is carried out with the help of two algorithms, namely the Decision Tree and Artificial Neural Network (ANN), by identifying the customer profile criteria obtained from the prediction of credit offers to customers. Both algorithms are evaluated using three parameters, namely gain ratio, confusion matrix, and Receiver Operating Characteristic (ROC). The Decision Tree produces the highest accuracy performance value of 99,34%, and AUC of 0, 998. Meanwhile, the ANN algorithm produces the highest accuracy of 99,13%, and AUC of 0.969. From each of these algorithms, it can be known about the effect of the treatment carried out on each parameter, and the effect on the performance results obtained.

Keywords
Credit, Data Mining, Decision Tree, Artificial Neural Network.

1. Introduction

A bank is one of the providers of various financial services for the community, one of which is credit. According to the Law of the Republic of Indonesia Article 1 Number 10 of 1998, credit is a claim or provision of money which can be stated to be the same, between a bank and other parties, by requiring the other parties to pay the bill within a predetermined period time. In the process, banks often experience problems in the process of returning money or filling bills by customers by following per under agreed terms. Therefore, it is very important to identify and evaluate credit applications made by customers (Hadianto et al., 2019), and monitor customers through historical data, so that banks can take preventive actions to avoid existing credit risks (Ivandari, 2015; Pandie, 2018; Rani, 2015).

To address this problem, this study aims to classify customers who have the opportunity to apply for and not apply for credit to a bank by using the customer profile which is taken from historical data owned by the bank. Classification is a process to determine data patterns to determine a group that has the same pattern. This classification is carried out with the help of data mining technique. Data mining is a process that is carried out to find hidden information in data, either in the form of relationships or patterns, and the purpose is not only to classify but also to process data based on clustering approach and visualization (Fiskas, 2017). This study uses data mining since this technique is able to extract information more quickly or automatically, especially on large quantities of data, so that the required processing time is shorter and more efficient.

There are two data mining algorithms used to assist the evaluation process, namely Decision Tree and Artificial Neural Network (ANN). Decision tree is one of the most widely used algorithms in research, because of the ease of processing IT, and its ability to process either categorical or numeric data (Larasati et al., 2019). Meanwhile, ANN is an algorithm that is composed of three layers, namely the input layer, hidden layer, and output layer (Larasati et al., 2019). ANN has also been widely used for data mining process because it provides accurate results for credit risk assessments (Mohammadi and Zangeneh, 2016). Both algorithms are evaluated using three parameters, namely confusion matrix, Receiver Operating Characteristics (ROC) curve by looking at the Area Under Curve (AUC) value obtained, and the gain ratio. As a result, this research produces the characteristics of the customer profiles in each of the two groups being evaluated so that the results can be used by the bank in making credit application decisions and also helps the bank avoiding losses from credit risk incurred by customers.

2. Literature Review

Credit is one of the services that own fairly high risk, so it is necessary to monitor the process. Supervision of credit is one of the bank's internal supervisory processes, starting from the time the customer submits a loan to the deadline for repayment (Andriani and Susanto, 2019). The purpose of the supervision is to ensure that there are no violations by the customers in accordance with the credit agreement. So, it is very important to carry out credit supervision to ensure that banks do not get risks because credit is one of the main income for a bank (Andriani and Susanto, 2019). This supervision can also be seen from the principle of credit, namely the 5C analysis (character, capacity, capital, collateral, and economic conditions). Supervision is carried out by looking at customer profile data owned by the bank. This profile can be in the form of a customer's average income (Windarto et al., 2017), occupation, number of family dependents, age, and others.

In accordance with the objectives of this study, the customer profile data is processed by classifying the profiles of the bank's customers. The goal is to find out whether the customer has a high opportunity to apply for credit or not. Classification aims to group data into a certain class according to their respective characteristics (Rani, 2015). This classification is carried out in two stages, namely the learning and classification stages. The learning stage is used to form a classification model, and the classification stage is the stage to apply the model that has been formed (Sartika and Indra, 2017). There are several commonly known classification algorithms, for example, *decision tree, nearest neighbor, neural network, support vector machine,* and *naïve Bayes.*

Classification is performed using data mining methods. Data mining has been widely used to obtain information or knowledge from data, or identify patterns within data (Iriadi and Nuraeni, 2016). Generally, data mining is used to process large amounts of data, because the results gets better when the data gets larger, and data mining can provide advantages for decision and strategy processes (Abdillah et al., 2016). Organizations use data mining to extract information on their database data and used this information to support the decisions that are need to be taken (Larasati et al., 2019).

There are two algorithms used to assist the classification process, namely the Decision Tree and Artificial Neural Network (ANN). A Decision Tree is an algorithm that is able to process either numeric or categorical data (Larasati et al., 2019), and a decision tree is built based on the gain ratio value generated from the attributes used (Saleh and Maryam, 2019). This gain ratio is used to see the best attributes in a group within a decision tree that produces the smallest size (Setiawan, 2019).

The decision tree has the advantage of being able to perform good classification because the results displayed are easy to understand even in complicated tree, and the error rate is quite small (Kim, 2016; Mohammadi and Zangeneh, 2016). Furthermore, Decision Tree is a powerful and flexible algorithm for the knowledge discovery (Mohammadi and Zangeneh, 2016). However, overfitting is one of the drawbacks of this algorithm that makes the tree results obtained do not provide good enough information (Badrul, 2016).

Meanwhile, ANN is one of the algorithm that can be either unsupervised or supervised learning (Nasser and Abu-Naser, 2019). ANN is a classification algorithm that can produce a good performance, can be applied to large quantities of data, and various kinds of problems because its ability to analyze a complex patterns in data (Ahlemeyer-Stubbe and Coleman, 2014; Bilal Z., 2016). ANN consist of three main layers there are input layer, hidden layer, and output layer (Bilal Z., 2016). ANN is shaped like a network structure with several layers, where the structure is arranged of nodes and continues to develop during the learning process (Hadianto et al., 2019).

The algorithm is evaluated using gain ratio, confusion matrix, and Receiver Operating Characteristics (ROC) parameters. The gain ratio is used to determine the attribute with the highest entropy value so that it can be selected as the main node (Setiawan, 2019). The confusion matrix provides information about the performance of the algorithm used (Ratri, 2017). The Confusion Matrix consists of four parts, namely, True Negative (TN), False Negative (FN), True Positive (TP), True Negative (TN). The ROC is used to evaluate the resulting Area Under Curve (AUC) value, the closer the resulting value to 1, the better the classification model.

3. Methods

In this study, the data used are secondary data taken from a machine learning repository. The data used consists of 14 variables with a total of 5000 customer data. The variables consist of five binary data variables, five interval data variables, two ordinal data variables, and two nominal data variables. List of variables used in this study is shown in Table 1. During the pre-processing step, two variables, namely ZIP code and customer ID, were excluded, since those two variables do not provide significant information on the stated research objectives. Then, all of these data are cleaned of the missing values and redundancy to avoid bias in the results obtained.

Table 1. Variable Data

No.	Variable	No.	Variable
1	ID Customer	8	Education
2	Age	9	Mortgage
3	Experience	10	Securities Account
4	Income	11	CD Account
5	ZIP Code	12	Online
6	Family	13	Credit Card
7	CC Average	14	Personal Loan (Y) / Dependent variable

This study uses RapidMiner software and applies several operators that this software has, for example, the select attribute to select the variables to be used, set roles to determine labels, split data to provide ratios to the formed partitions, cross-validation to validate on the training and testing data used, etc. Furthermore, cross-validation is used to estimates the accuracy or performance of the model (Keramati et al., 2016).

Cross-validation has a random seed parameter, where these parameters are used to be able to maintain the value used in the data partition against the applied variable, so that the value of the variable used can be constant. If the variables used are constant, then the next step is to select the best parameter to ensure the best results are obtained. In this study, the default value of a predetermined random seed is used.

The setting parameter for Decision Tree and ANN algorithms can be seen in Table 2 and Table 3, while the description of each ANN parameter is shown in Table 4.

Table 2. Parameters of Decision Tree Algorithm

Parameters	Value
Criterion	Gain Ratio
Maximal depth	10
Confidence	0.2
Minimal gain	0.02
Minimal Leaf size	1
Minimal size for split	4
Number of pre-pruning	3
Split ratio	0.6: 0.4

Table 3. Parameters of ANN Algorithm

Parameters	Value
Training Cycle	100 until 1000
Learning rate	0.1 until 1
Momentum	0.1 until 1
Hidden Layer	12 until 36 *nodes*

Table 4. Description of ANN Parameters

Parameters	Value	Description
Training cycles	1000	Used to determine the number of repetitions *training* that must be done to produce the *error* smallest with values ranging from 1 to infinity (Badrul, 2016)
Learning rate	0.1	The parameters used to determine the weights of *neurons* with a value in the form of a positive number less than 1
Momentum	0.28	Parameter to be able to accelerate the *learning rate,* increase *convergence* with values ranging from 0 to 1 (Badrul, 2016)

4. Results and Discussion

Following are the results of the analysis that has been carried out for the two algorithms:

4.1 Decision Tree Algorithm

In this algorithm, the first step is to determine the split ratio value that results in the highest accuracy value with the default parameter value. There are three types of ratio values used (can be seen in Table 5). The total number of attributes are nine. The results of Table 5 states that a split ratio of 0.6: 0.4 produces the highest accuracy value of 99.22%, and AUC = 0.974, and it reflects that the classification results obtained are very good. Therefore, this ratio value is used in the next process.

Table 5. Comparison of Accuracy Result on The Split Ratio Operator

Split Ratio	Accuracy	AUC
0.6: 0,4	**99.29%**	**0.974**
0.7: 03	99.25%	0.998
0.8: 0,2	99.06%	0.996

Then, the second stage is to treat the five parameters used, namely minimum size for split, minimum gain, minimum leaf size, number of pre-pruning, and confidence. The experiment is performed at 16 iterations The results is shown in Table 6. This result indicates that the 6th iteration delivers the highest accuracy value, which is 99.34%, with AUC = 0.998. The accuracy and AUC (Figure 1) values shows that the classification model used is very good, because the accuracy value exceeds 90%, and the AUC value is close to 1.

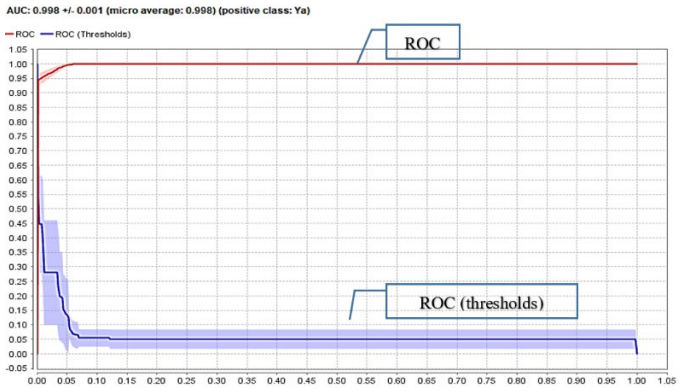

Figure 1. AUC of Decision Tree Algorithm

Table 6. Result of Decision Tree Parameters

Num.	Confidence	Minimal Gain	Leaf Size	Size for Split	Number Pre-pruning	Accuracy	AUC
1	0.1	0.01	1	1	1	99.28%	0.997
2	0.1	0.02	2	2	2	99.08%	0.992
3	0.1	0.03	3	3	3	98.69%	0.968
4	0.1	0.04	4	4	4	98.81%	0.994
5	0.2	0.01	2	3	4	99.30%	0.998
6	**0.2**	**0.02**	**1**	**4**	**3**	**99.34%**	**0.998**
7	0.2	0.03	4	1	2	98.64%	0.954
8	0.2	0.04	3	2	1	98.72%	0.970
9	0.3	0.01	3	4	2	98.61%	0.968
10	0.3	0.02	4	3	1	98.48%	0.951
11	0.3	0.03	1	2	4	99.28%	0.997
12	0.3	0.04	2	1	3	99.17%	0.997
13	0.4	0.01	4	2	3	98.48%	0.951
14	0.4	0.02	3	1	4	99.01%	0.996
15	0.4	0.03	2	4	1	98.87%	0.990
16	0.4	0.04	1	3	2	99.01%	0.995

The following are the performance of the model obtained in the form of confusion matrix, where Table 7 provides information about the performance for the training data used, and Table 8 describes the performance of the testing data.

Table 7. Performance Training Decision Tree

	***true* No**	***true* Yes**	***class precision***
pred. No	24382	160	99.35%
pred. Yes	17	2441	99.31%
class recall	99.93%	93.85%	
Accuracy	99.34%		

Table 8. Performance Testing Decision Tree

	***true* No**	***true* Yes**	***class precision***
pred. No	2692	42	98.46%
pred. Yes	19	247	92.86%
class recall	99.30%	85.47%	
Accuracy	97.97%		

In addition to performance, there are precision and recall values which can be seen in Table 9 and Table 10, and the resulting tree output (Figure 2) is as follows:

Table 9. Precision Decision Tree

	***true* No**	***true* Yes**	***class precision***
pred. No	24382	160	99.35%
pred. Yes	17	2441	99.31%
class recall	99.93%	93.85%	
Precision	99.31%		

Table 10. Recall Decision Tree

	***true* No**	***true* Yes**	***class precision***
pred. No	24382	160	99.35%
pred. Yes	17	2441	99.31%
class recall	99.93%	93.85%	
Recall	93.85%		

For the Decision Tree algorithm, there is a change in the parameters of the treatment carried out on the parameters used. First, when the confidence parameter value is at the smallest value, namely 0.1, the minimal gain value increase, but the other three parameters are of equal value, the higher the value for the three parameters, the smaller the resulting accuracy. The resulting gain value should be minimized as much as possible because it can minimize the experiment that must be carried out, increase the resulting variation, and the tree can be simpler (Han et al., 2012).

Furthermore, when the confidence value increases, the resulting accuracy value tends to decrease. This result is in line with Putri and Waspada (2018) who conclude that the higher the confidence value, the lower the accuracy of the model. When the confidence value tends to be higher, a node with high error can be tolerated to be used in the tree structure formation process. Also, this study finds that there is a relationship between the minimum gain and the size for split, thus, when the minimum gain value is low and the size for split is high, the accuracy tends to be high, and vice versa.

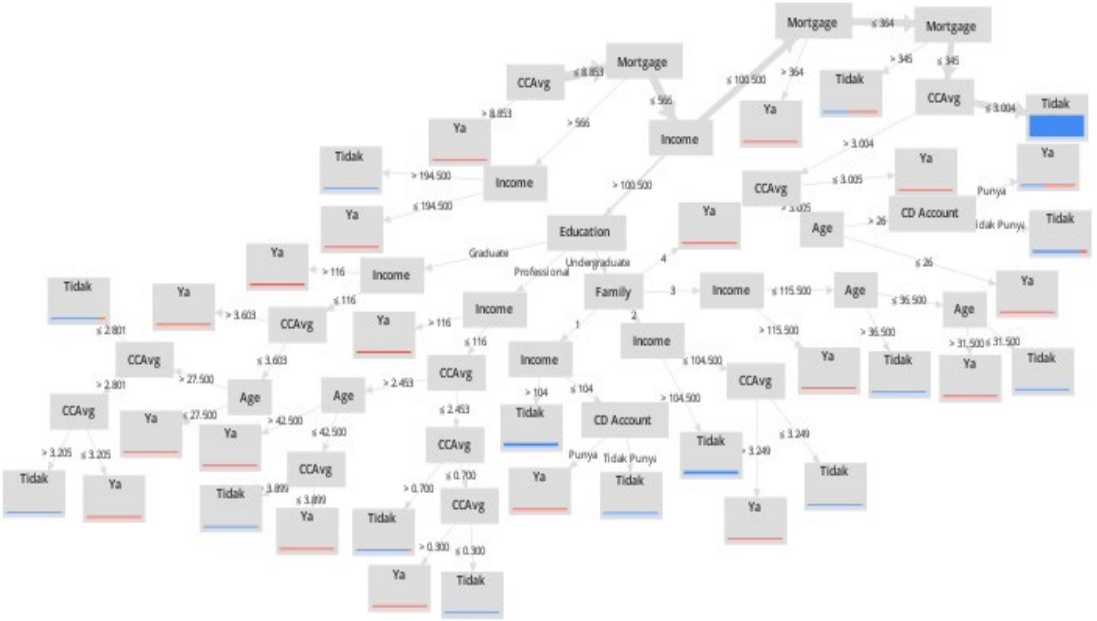

Figure 2. The Result of Decision Tree

Then, if the value on the number of pre-pruning gets bigger, accuracy tend to be higher. If associated with minimum leaf size with a low value, the resulting accuracy value also tend to be higher. Pruning is used to reduce the number of tree which does not provide significant information on the target variable, so that the accuracy obtained is higher and prevent overfitting of the model (Ahlemeyer-Stubbe and Coleman, 2014; Lukito and Chrismanto, 2015). Also, pre-pruning is able to reduce the error rate so that the model accuracy can be higher (Kim, 2016). In addition, if the value of the leaf size is increased, the accuracy is decrease. The greater the value given to the leaf size, the greater the number of leaves formed on the tree. When leaf size that is too large, it tends to hamper the tree formation process.

4.2 Artificial Neural Network Algorithm

The optimize parameter operator is used at the initial stage of parameter determination is shown in Table 11. Table 11 shows that the best accuracy value is 99.24%, which is achieved in the 5th iteration. The use of the operator *optimize parameters* on several algorithms aims to increase the percentage value of model performance (Tantithamthavorn et al., 2018).

Table 11. Parameter Value Determination

No	Training cycle	Learning rate	Momentum	Accuracy
1	**100**	**1**	**0.1**	**98.40%**
2	300	1	0.55	98.20%
3	500	0.775	0.325	98.20%
4	700	0.1	0.775	98.10%
5	900	0.775	0.775	98.30%

The next step is to carry out 10 iterations by treating the hidden layer size (node) using the previous parameter values. This study uses nine variables, so that the minimum number of nodes used is a number of existing input variables, and the maximum is three times the number of variables used. The results of the treatment on the hidden layer size is shown in Table 12, and the resulting ANN structure image is in Figure 3. Based on Table 12, the 7th iteration results in the highest accuracy with the total of hidden layer size is 21, performance training set = 99.14%, performance testing set = 98.07%, and AUC = 0.969.

Table 12. Determination of The Number of Hidden Layer Models

Num.	*Hidden Layer Size*	Perform. Training	Perform. Testing	AUC
1	9	98.75%	97.73%	0.967
2	11	98.76%	97.57%	0.969
3	13	98.74%	97.90%	0.969
4	15	98.87%	98.10%	0.970
5	17	98.92%	97.93%	0.969
6	19	98.94%	98.30%	0.970
7	**21**	**99.13%**	**98.07%**	**0.969**
8	23	99.03%	97.80%	0.972
9	25	98.97%	98.37%	0.970
10	27	98.91%	98.00%	0.969

Table 13. Performance Training of ANN

	true No	*true* Yes	*class precision*
pred. No	24357	192	99.22%
pred. Yes	42	2409	98.29%
class recall	99.83%	92.62%	
Accuracy	99.13%		

Table 14. Performance Testing of ANN

	true No	*true* Yes	*class precision*
pred. No	2699	46	98.32%
pred. Yes	12	243	95.29%
class recall	99.56%	84.08%	

Accuracy	98.07%	

The confusion matrix is shown in Table 13 for performance of training model, and Table 14 for performance testing model. In addition, Table 15 presents the results for precision, and Table 16 for the results of recall of the ANN model.

Table 15. Precision of ANN

	***true* No**	***true* Yes**	***class precision***
pred. No	24357	192	99.22%
pred. Yes	42	2409	98.29%
class recall	99.83%	92.62%	
Precision	98,31%		

Table 16. Recall of ANN

	***true* No**	***true* Yes**	***class precision***
pred. No	24357	192	99.22%
pred. Yes	42	2409	98.29%
class recall	99.83%	92.62%	
Recall	92.62%		

In ANN model with the best performance results, it shows that the higher number of the *training cycle* produces a better accuracy value since the *training cycle* is used to reduce errors in data, so that the more iterations, the better the accuracy value obtained (Badrul, 2016). In the parameter *learning rate,* when the higher the learning rate parameter, the faster the iteration process. However, it may cause oscillations in the weight and reduce the accuracy value obtained (Badrul, 2016). Conversely, the lower the *learning rate* given, the higher the accuracy gotten. Then, the parameter *momentum* is used to shorten the time learning process *(learning)* in order to reduce oscillations in the weight (Badrul, 2016). To overcome this problem, choosing the right attribute can be the solutions, because larger number of attributes may decrease the accuracy. Generally, the value of *learning rate* is inversely proportional to the value of *momentum* in order to get the best accuracy value.

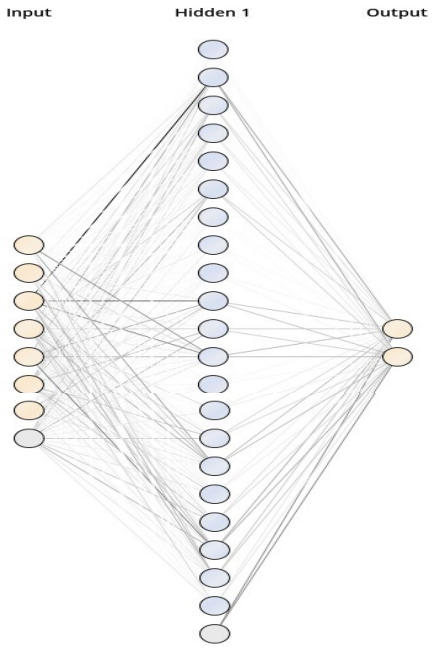

Figure 3. ANN Structure

The results of the study indicates that ANN provides lower accuracy than the Decision Tree, but still the accuracy of the ANN model can be categorized as very high. In the field of commerce, Azad's research (2016) also finds that Neural Networks can provide good accuracy results in determining e-commerce adoption. However, ANN has the disadvantage that the modeling process takes longer than the Decision Tree. In addition, ANN does not provide direct information about the relationship between variables because it is hidden in the resulting structure (Bilal, 2016).

The treatment for the number of hidden layer nodes is carried out in order to see the best results from the model. Determining the number of hidden layer nodes is good because it can avoid excessive learning in training data, so that the model can give the best results according to the problem. When the number of nodes in the hidden layer is too high, the data training process usually takes longer or the model tends to be overfitting because the information in the training data set cannot train all nodes in the hidden layer. In contrast, when the selected node is too low, the complexity and the relationship between the resulting input-output is not optimally obtained or an underfitting of the model occurs (Badrul, 2016; Mohammadi and Zangeneh, 2016). Within the hidden layer, it is hard to predict what kind of the output that can be produced, because the feature activation cannot be fully understood in terms of the cause and effect relationships, also the results obtained from setting the feature activation are depend on the effects of other nodes in that layer (Frosst & Hinton, 2018).

Decision Tree Algorithm produces highest performance compared to ANN, because decision tree is an algorithm that has a fast processing relatively to other classification algorithm (Sharma & Kumar, 2016). In the pruning process, the algorithm can reduce or cut the tree that are not needed, and replacing them with the leaf node. This algorithm produces the best conclusions from the data by generating a tree that provides the most important information from the data, so that it can have an impact in the performance value. Frosst and Hinton (2018), state that the node in the lower levels of decision tree just only are used by a very small parts of the training data and tend to overfit the model, unless the training set has exponentially large compared with the depth of the tree.

Furthermore, decision tree also can produce a small performance due to changes in several data variables used. As Mohammadi and Zangeneh (2016), state that the Decision Tree can provide unstable results, especially if there are small changes in the data that can affect the overall classification results obtained. A result tree that is too large or complex can also provide difficulties in the interpretation process that must be carried out. So, adjustments are made to produce a tree that is not too big or complicated. So, it can be said that the performance of the algorithm depends on the variables and parameter settings. Therefore, it is recommended to do a combination experiment on each parameter setting to be able to produce the best performance model.

5. Conclusions

The results of the research show that the Decision Tree produces a higher performance value compared to ANN. The accuracy performance obtained by the Decision Tree is 99.36%, AUC = 0.999, precision = 99.32%, and a recall of 94.00%. Meanwhile, ANN has an accuracy value of 98.34%, AUC = 0.978, precision = 94.16%, and recall = 87.11%. The results of the Decision Tree are obtained from the use of minimum gain parameters of 0.05, minimum leaf size = 2, split ratio = 0.6 (60%), the minimum size for split = 3, confidence = 0.2, and a number of pre-pruning = 4. Then, the parameters of ANN used to produce the highest accuracy results are learning rate = 0.3, training cycle = 600, and momentum = 0.1.

In the ANN algorithm, these results are obtained from several iterations, where the higher the training cycle parameter value, the higher the accuracy. Furthermore, if the learning rate increase, the resulting accuracy decrease. Then, the determination of the momentum value and the learning rate must be set inversely to produce the best accuracy value. In addition, it is necessary to make the correct selection of the hidden layer node values to avoid overfitting or underfitting the model, causing the model to be unable to provide significant information.

Whereas in the Decision Tree algorithm, the lower accuracy is obtained when the minimum gain value is higher, the confidence at the minimum value, and the three other parameters are equal. In addition, when the confidence increases, the accuracy tends to decrease. Then, when the minimum leaf size is low, the number of pre-prunning is high, the accuracy tends to increase. Finally, if the minimum leaf size value is set high, the accuracy is

proportionally low. Furthermore, when the size for split value is high, while the minimal gain is low, the resulting accuracy tends to be high. Therefore, for the two variables it is very necessary to make adjustments to each parameter to be able to increase the value of the accuracy or performance of the model used.

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