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Analysis of Data Classification Accuracy Using ANFIS Algorithm Modification with K-Medoids Clustering

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Abstract: The ANFIS algorithm is a technique in data mining that can be used for the data classification process. The ANFIS algorithm still has weaknesses, especially in determining the initial parameters for the network training process. Thus, an additional algorithm or modification is needed for the determination of these parameters. In this study, a clustering method will be proposed, namely K-Medoids Clustering as an additional method to the ANFIS algorithm. Basically, the ANFIS algorithm uses the FCM (Fuzzy C-Means Clustering) algorithm for the initial initialization of network parameters. The use of this method can cause local minima problems, where the clustering results obtained are not optimal because the pseudo-partition matrix generation process is carried out randomly. The matrix value will determine the initial parameter value in the ANFIS algorithm used in the first layer. Based on the research that has been done, it can be concluded that the accuracy of data classification using the ANFIS algorithm which has been modified with the proposed method provides a fairly good influence in conducting training and classification testing. The increase that occurs in the proposed method is 0.73% for the average training accuracy and an increase of 0.66% for the average testing accuracy.

Keywords: ANFIS, FCM, K-Medoids Clustering, Classification, Accuracy

INTRODUCTION

The ANFIS (Adaptive Neuro Fuzzy Inference System) algorithm is a technique in data mining that can be used for the data classification process. The ANFIS algorithm has successfully solved various engineering and real-world problems in various applications, such as: system identification and modeling, process control, system diagnosis, cognitive simulation, classification, pattern recognition, image processing, engineering design, financial trading, signal processing, time prediction, forecasting and others (Bushara & Abraham, 2015). The ANFIS algorithm is an efficient combination of ANN (Artificial Neural Network) and FL (Fuzzy Logic) for high, complex and dynamic non-linear modeling systems (Salleh & Hussain, 2018).

Several researchers in the research that has been done prove that the ANFIS algorithm has better performance compared to other methods. Research conducted using the ANFIS learning model is able to capture the dynamics of rainfall data behavior and achieve satisfactory results, so it is useful in predicting long-term rainfall. In this study, the use of the ANFIS algorithm obtained results with a smaller error rate than the Back Propagation Neural Network algorithm (Bushara & Abraham, 2015). Another study conducted temperature predictions using the ANFIS and ARIMA models. The results showed that the ANFIS model had smaller RMSE and MSE compared to other models (Septiarini & Musikasuwan, 2018).

The learning process in the ANFIS algorithm is generally carried out by involving gradient-based learning which is prone to local minima problems. Despite gaining popularity among researchers, implementation of the ANFIS based model faces problems when the number of rules increases dramatically and increases the complexity of the network which consequently increases the computation time. Basically, not all rules in the ANFIS knowledge base are potential rules (Hussain & Salleh, 2016).There are many studies that have used meta-heuristic algorithms to set the initial parameters of the ANFIS algorithm. This research has modified the architecture of the ANFIS algorithm to reduce time complexity and increase classification accuracy (Salleh & Hussain, 2018).

The research was conducted to try various types and forms of membership functions as well as the ABC (Artificial Bee Colony) meta-heuristic algorithm combined with the ANFIS algorithm. The results show that the modified ANFIS combined with the ABC method provides higher training results compared to the general ANFIS model (Salleh & Hussain, 2018). Another study compared the performance of the general ANFIS algorithm with the combination of the ANFIS algorithm using the SC (subtractive clustering) algorithm in predicting the water quality

*name of corresponding author

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index. Based on the evaluation carried out, it was found that the combination of the ANFIS algorithm gave more accurate results than the general or conventional ANFIS method (Tiwari & Kaur, 2018).

Based on the research that has been described previously, the ANFIS algorithm still has weaknesses, especially in determining the initial parameters for algorithm training. Thus, an additional algorithm or modification is needed for the determination of these parameters. In this study, a clustering method will be proposed, namely K-Medoids Clustering as an additional method to the ANFIS algorithm. Basically, the ANFIS algorithm uses the FCM (Fuzzy C-Means Clustering) algorithm for the initial initialization of network parameters. The use of this method can cause local minima problems, where the clustering results obtained are not optimal because the pseudo-partition matrix generation process is carried out randomly. The matrix value will determine the initial parameter value in the ANFIS algorithm used in the first layer.

K-Medoids Clustering in this study will be used to replace the FCM (Fuzzy C Means Clustering) method for the clustering process used in the ANFIS algorithm. The better the clustering process, the better the classification results obtained using the ANFIS algorithm. K-Medoids Clustering is a better data clustering method than K-Means Clustering on heterogeneous data. The use of this algorithm is done because the results of the grouping have good performance on heterogeneous data sets with varying data types (Harikumar & Surya, 2015). Therefore, this study will modify the ANFIS algorithm with K-Medoids Clustering for data classification cases. The results obtained will be analyzed and compared with the ANFIS algorithm without modification.

LITERATURE REVIEW

Classification

Classification is a technique of grouping data in data mining with the aim of finding class labels on a data set or dataset through a learning process on predetermined training data. The algorithms used to solve classification problems are categorized into supervised learning (Sivakumar, Venkataraman & Bwatiramba, 2020) Supervised learning in its application has a class label on the training data and then predicts the class label on new data or data whose class label is unknown using a classification algorithm. Several algorithms are used for the data classification process, such as: Decision Trees, Neural Networks, Support Vector Machines, Naives Bayes, ANFIS and others.

The training process on the classification algorithm by mapping each input set or attribute x to one of the y classes that have been defined previously. The input to the classification algorithm is a set of training sets from each record consisting of a set of attributes and one of the attributes is the data class label (Verma, 2018). The class attribute is required as a function of the values in the other attributes and is used in the following cases:

1 Descriptive modeling is a description that is done to distinguish objects from different classes.
2 Predictive modeling is the prediction of a class label for data or records whose class label is unknown.

Classification in data mining can be done based on historical data or past data. Historical data is also known as training data or training set. This data is used as a process to gain knowledge or also known as experience data (Alaoui & Aksasse, 2018). In simple terms there are 3 things that are needed in solving classification problems including:

1 Historical data or experience data obtained previously. This data can be in the form of rainfall data, observational data and others.
2 Classification algorithm used as a problem solving process in grouping data.

Classification results that generate knowledge or in the form of class labels from new data or test data.

ANFIS (Adaptive Neuro-Fuzzy Inference System)

ANFIS (adaptive neuro-fuzzy inference system) is a data classification algorithm with an architecture that is functionally similar to Sugeno's fuzzy rule base model. This method is a combination of methods with the working principle of the Fuzzy Inference System and artificial neural networks. This combination is done because it can minimize the weaknesses of each method by using numerical data to predict the output that produces a better effect (Sönmez, Kale, Ozdemir & Kadak, 2018).

The basis for combining the two methods is taken from the advantages of the method used. Fuzzy Inference System (FIS) has the advantage of modeling the qualitative aspects of human knowledge and as a process for making decisions by applying the rule base. Meanwhile, ANN has the advantage of recognizing patterns, the training process in solving a problem without the need for mathematical modeling and can work based on historical data entered and can predict new data based on previous data. This combination makes the ANFIS algorithm have both capabilities (Jang & Mizutani, 1997).The ANFIS work step or process consists of five layers, namely: fuzzification layer, rule layer, normalization layer, defuzzification layer and single neuro results (Ata & Kocyigit, 2010).

The working principle of the ANFIS algorithm is similar to how an artificial neural network works, but it has five layers, as shown in Figure 1 as follows (Roy, Sadhu, Bandyopadhyay, Bhattacharyya, D. & Kim, T, 2016):

*name of corresponding author

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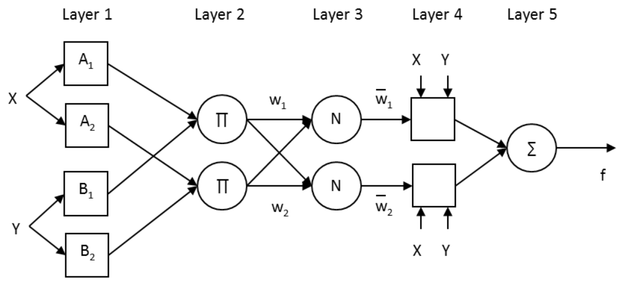

Fig. 1. ANFIS Network Architecture.

The explanation of each layer in the ANFIS algorithm can be described as follows :

Layer 1

The first layer is a layer that functions to convert crisp numbers or values into fuzzy numbers using fuzzy sets. The output of this process can be seen in the following equation:

$$O_i^1 = \mu_{A_i}(x), \quad \text{for } i = 1, 2 \tag{1}$$

Layer 2

The second layer is a layer that functions to determine the firing strength of each input. Fuzzy Sets are multiplied between one input and another with the relationship using the following equation:

$$O_i^1 = w_i = \mu_{A_i}(x) * \mu_{B_i}(y), \quad \text{for } i = 1, 2 \tag{2}$$

Layer 3

The third layer is a layer that functions to perform normalization calculations before being applied to the fourth layer. Normalization is a re-weighting process in order to obtain a total/max value of one using the following equation:

$$O_i^1 = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad for\ i = 1, 2 \tag{3}$$

Layer 4

The fourth layer is a layer that functions to multiply by functions involving inputs (x and y) to produce crisp output using the following equation:

$$O_i^1 = \bar{w}_i * f_i = \bar{w}_i(p_i * x + q_i * y + r_i) \tag{4}$$

Layer 5

The fifth layer, is a layer that functions to accumulate the results of the fourth layer (for two rules) using the following equation:

$$O_i^1 = \sum \bar{w}_i * f_i = \frac{\sum_i w_i * f_i}{w_i} \tag{5}$$

K-Medoids Clustering

K-Medoids Clustering or also known as Partitioning Around Method (PAM) is a non-hierarchical cluster method and is also an alternative to the K-Means Clustering method (Soni & Patel, 2017). The difference between this method and the K-Means Clustering algorithm lies in the determination of the data cluster center. The K-Means Clustering algorithm uses the average value (means) of each cluster as the center of the cluster and the K-Medoids Clustering algorithm uses data objects as representatives (medoids) as the center of the cluster (Kaur, & Singh, 2014).

K-Medoids Clustering applies the partition grouping method to group a set of n objects or data into a number of k clusters (Shamsuddin & Mahat, 2019). This algorithm uses some objects or data that are used as representatives in the data set to represent a cluster. Objects or data used to represent a cluster are also called medoids. Medoids are objects or data that are located centrally in a cluster so that they are more resistant to outlier data. Clusters are built by calculating the proximity of the medoids to objects or data that are not medoids.

METHOD

This study proposes a method that can improve the accuracy of data classification in the ANFIS algorithm using the K-Medoids Clustering method in determining the data cluster center which was previously carried out using the FCM (Fuzzy C-Means Clustering) method. K-Medoids Clustering is one of the clustering algorithms that is quite popular among researchers and has reliability in grouping data. The results or outputs of the method are the results of data clustering and data cluster centers which are used as initial parameters in the ANFIS algorithm.

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Inappropriate initial parameter selection in the ANFIS algorithm can reduce the accuracy of data classification. The problem that often arises in the algorithm is the local optima case, where the function point produces the lowest output. This is because the final result of the cluster obtained is not in accordance with the original characteristics of the existing cluster. The proposed research steps can be seen in Figure 1 as follows.

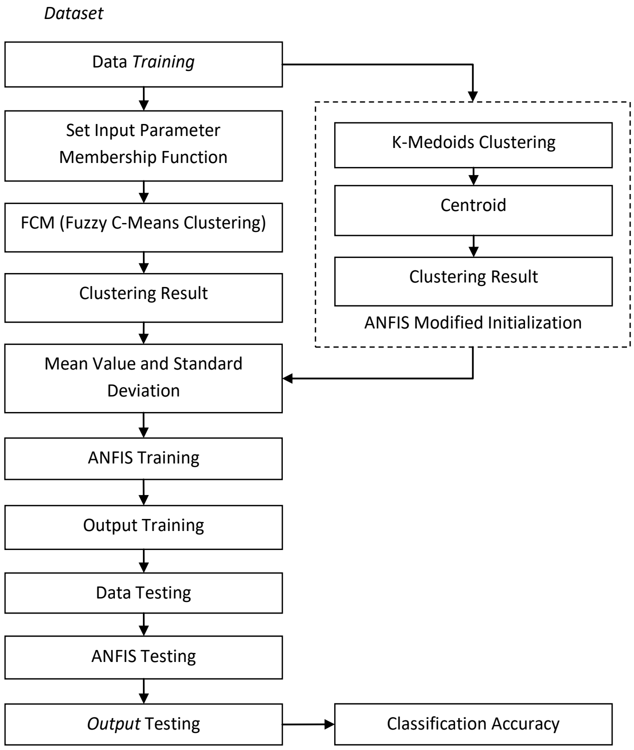

Fig. 2. Proposed Method Flowchart.

The following are the proposed research steps for data classification using the modified ANFIS (Adaptive Neuro-Fuzzy Inference System) algorithm with K-Medoids Clustering, including:

Datasets
Is the data used for the process of testing the data classification algorithm using a modified ANFIS algorithm with K-Medoids Clustering. The datasets in this study will be divided into two, namely training data and testing data with a percentage of 70: 30.

Training data
Is data that is used as network input for learning the ANFIS algorithm. The results will be obtained in the form of parameters for testing the ANFIS algorithm.

Initialization of FCM parameters
Is the initial parameter used for the training process on the ANFIS algorithm. In this study, these parameters will be obtained using a random method. The process of determining the initial parameters that are not appropriate can result in minimal local problems on the classification results, so additional or modification methods are needed to obtain the appropriate initial parameters.

The FCM
Algorithm is a method in the ANFIS algorithm that is used for the data clustering process that is used as the ANFIS network input.

K-Medoids Clustering Algorithm
Is a modified method used to replace the FCM method in the ANFIS algorithm. This method is used for the data clustering process that is used as input for the ANFIS network.

*name of corresponding author

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The data cluster center
Is the result of clustering performed with the FCM algorithm and K-Medoids Clustering. The resulting cluster center is in the form of data that determines the results of grouping the entered data.

The average value and standard
Deviation are the values used for the ANFIS network training process.

ANFIS network training
Is a process carried out to obtain network testing parameters. This process is done by applying 5 layers or layers to the ANFIS algorithm.

ANFIS parameter
Is the final value or optimum parameter as a result of training on the ANFIS algorithm. This value will be reused for the ANFIS algorithm testing process.

Testing data
Is the data used for the ANFIS algorithm testing process. The data will be inputted on the network and grouped based on the attributes and parameters generated previously.

ANFIS network output
Is the result of classification or grouping resulting from the testing process based on the input test data.

Accuracy of data classification
Is a process to calculate the results of the accuracy of the calculation data from the proposed method with the actual results. This is done to find out how influential the modification of the method has been so that a conclusion can be drawn.

Accuracy analysis
Is a process carried out to see and explain the results of the comparison of accuracy and error values obtained using the modified ANFIS network method with K-Medoids Clustering and the regular ANFIS network. This process is carried out based on the test results of the method carried out and describes in detail the effect of the K-Medoids Clustering method in the ANFIS network.

In analyzing the accuracy of data classification using the modified ANFIS algorithm with K-Medoids Clustering, the data used is in the form of classification data from 3 different datasets. The datasets were obtained from the internet page with the address https://archive.ics.uci.edu/ml/datasets/ which is shown in Table 1 below.

Tabel 1 Dataset

No.	*Names of Data*	*Instances*	*Features*
1	Wisconsin Breast Cancer	569	32
2	Pima Indians Diabetes	768	9
3	High Time Resolution Universe (HTRU2)	17898	9

RESULT

In this section, testing will be carried out on dataset I to dataset III using the usual ANFIS algorithm and using a modified ANFIS algorithm with the K-Medoids Clustering method.

The Results of ANFIS Training

Tests were conducted to compare the accuracy of data classification using the ANFIS algorithm without modification and the modified ANFIS algorithm method with K-Medoids Clustering. The data will be divided into two parts, namely training data and test data with a percentage ratio of 70: 30.

At the initial stage, the training data will be clustered using a clustering algorithm with 2 clusters, namely: 0 and 1. This stage will produce 2 cluster center values which determine the average value and standard deviation. The next stage, the process of finding the average value and standard deviation value will be carried out to determine the value of the membership function in the ANFIS algorithm in the first layer. This value serves to determine the output value to the last layer in the ANFIS algorithm. The final stage of the process will produce parameters in the form of p, q and r values for the testing process on the ANFIS algorithm. The test accuracy of the ANFIS algorithm training results can be seen in Table 2 as follows.

*name of corresponding author

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Tabel 2 Accuracy Calculation Results of ANFIS Training

Datasets	*Number of Intances*	*The Result of Accuracy (%)*	
		ANFIS	*ANFIS_KMedoid*
I	398	84.17	84.92
II	538	72.30	73.05
III	12529	90.31	90.99
Average Acuracy		82.26	82.99

In Table 2, the average training accuracy obtained by modifying the ANFIS algorithm with K-Medoids Clustering obtained an accuracy of 82.99%. While the average accuracy of training with the usual ANFIS method obtained an accuracy value of 82.26%. This shows that the proposed method is higher than the usual ANFIS method by 0.73%.

The resulting accuracy value between the proposed method and the method in general does not differ too much. The difference lies in the initial training process of the ANFIS algorithm, namely the clustering method used. Generally, the ANFIS algorithm uses the FCM method in conducting the data clustering process. While the proposed method will replace the FCM algorithm with the K-Medoids Clustering method. In the third dataset, the accuracy value shows that the proposed modification method is able to carry out the training process on the ANFIS algorithm well.

The Results of ANFIS Testing

After conducting the training process on the ANFIS algorithm, the output parameter values will be obtained that will be used during the testing process for each method. The input value on the new data or testing data will be calculated with the parameter value until the output value of the testing process is obtained. The results of testing the two methods can be seen more clearly in Table 3 as follows.

Tabel 3 Accuracy Calculation Results of ANFIS Testing

Datasets	*Number of Intances*	*The Result of Accuracy (%)*	
		ANFIS	*ANFIS_KMedoid*
I	171	92.40	92.40
II	230	77.83	78.26
III	5369	94.71	96.24
Average Acuracy		88.31	88.97

In Table 3, the test accuracy obtained by modifying the ANFIS algorithm with K-Medoids Clustering obtained an average accuracy result of 88.97%. While the accuracy of testing with the usual ANFIS method obtained an average accuracy value of 88.31%. This shows that the proposed method is higher than the usual ANFIS method by 0.66%.

Based on the accuracy values of the three dataset tests obtained, the average accuracy can be calculated by adding up all the results of the training accuracy and the dataset test accuracy divided by the total data. This value will be compared between the ordinary ANFIS algorithm testing and the modified ANFIS algorithm using the K-Medoids Clustering method, so that the difference between the two methods can be seen.

In Table 2 and Table 3, it can be seen the differences in each test using the proposed method where the proposed method has a fairly good influence in conducting training and classification testing. The increase that occurs in the proposed method is 0.73% for training accuracy and an increase of 0.66% for testing accuracy. In order to make it easier to see the results of the differences between the two methods, the test results can be seen in Figure 3 as follows.

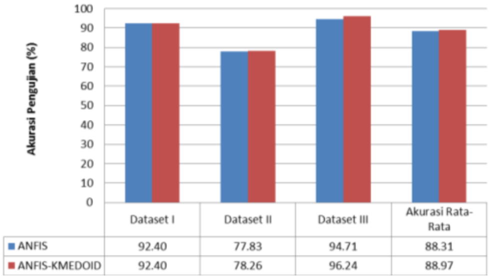

Fig.3. Comparison Method of Data Classification Testing Accuracy

*name of corresponding author

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In Figure 3, the results of the test accuracy for each dataset using the proposed method obtain improved classification results. Basically, the values obtained are not much different, because the method added to the ANFIS algorithm is a clustering method that is used directly without applying the pseudo-partition matrix value, such as the FCM method performed on the ANFIS algorithm. In the usual ANFIS algorithm, the maximum accuracy value can be obtained by determining the correct pseudo-partition matrix value. The pseudo-partition matrix value will continue to be updated until the best objective value is obtained or by determining the previously determined epoch value.

The Fuzzy C-Means Clustering Algorithm in ANFIS will determine the data cluster points of each data group formed from the training data. Each data group will produce one data cluster point, so that the number of cluster center points generated is as many as the data class. Furthermore, eachdata cluster center point will determine which class the data will be grouped into after calculating the final pseudo-partition matrix value. The use of pseudo-partition matrix values at the beginning of the algorithm training will determine the final classification results. The more precise this value is obtained, the better the classification results obtained and vice versa.

The K-Medoids Clustering method is basically a data cluster method similar to the FCM method. The difference lies in the process of determining the data centroid value and does not require a pseudo-partition matrix value. This method can be applied to the ANFIS algorithm, such as the FCM method. The final centroid value obtained will be used to obtain the average value and standard deviation of the ANFIS algorithm. The principle of this method is only to compare the objective values generated during the process of searching for the centroid value. This method can also minimize the shortcomings of the FCM method which is prone to local minima problems, where the clustering results obtained are not optimal because the pseudo-partition matrix generation process is carried out randomly.

Based on the explanation, it was explained that the proposed method by modifying the ANFIS algorithm using K-Medoids Clustering was able to increase the accuracy of data classification both in training and testing. This method can be used on both small and large datasets with different number of data rows and attributes. The results obtained that the use of the clustering method in the ANFIS algorithm which generally uses the FCM method can also be done using the K-Medoids Clustering method with better accuracy values.

DISCUSSIONS

The test accuracy obtained by modifying the ANFIS algorithm with K-Medoids Clustering obtained an average accuracy result of 88.97%. While the accuracy of testing with the usual ANFIS method obtained an average accuracy value of 88.31%. This shows that the proposed method is higher than the usual ANFIS method by 0.66%.

Based on the accuracy values of the three dataset tests obtained, the average accuracy can be calculated by adding up all the results of the training accuracy and the dataset test accuracy divided by the total data. This value will be compared between the ordinary ANFIS algorithm testing and the modified ANFIS algorithm using the K-Medoids Clustering method, so that the difference between the two methods can be seen.

It can be seen the differences in each test using the proposed method where the proposed method has a fairly good influence in conducting training and classification testing. The increase that occurs in the proposed method is 0.73% for training accuracy and an increase of 0.66% for testing accuracy. In order to make it easier to see the results of the differences between the two methods.

CONCLUSION

Based on the research that has been done, it can be concluded that the accuracy of data classification using the ANFIS algorithm which has been modified with the proposed method provides a fairly good influence in conducting training and classification testing. The increase that occurs in the proposed method is 0.73% for training accuracy and an increase of 0.66% for testing accuracy. The results obtained that the use of the clustering method in the ANFIS algorithm which generally uses the FCM method can also be done using the K-Medoids Clustering method with better accuracy values.

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