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Stability of classification performance on an adaptive neuro fuzzy inference system for disease complication prediction

Sri Kusumadewi[1], Linda Rosita[2], Elyza Gustri Wahyuni[1]
[1]Department of Informatics, Faculty of Industrial Technology, Universitas Islam Indonesia, Yogyakarta, Indonesia
[2]Faculty of Medicine, Universitas Islam Indonesia, Yogyakarta, Indonesia

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ABSTRACT

It is crucial to detect disease complications caused by metabolic syndromes early. High cholesterol, high glucose, and high blood pressure are indicators of metabolic syndrome. The aim of this study is to use adaptive neuro fuzzy inference system (ANFIS) to predict potential complications and compare its performance to other classifiers, namely random forest (RF), C4.5, and naïve Bayesian classification (NBC) algorithms. Fuzzy subtractive clustering is used to construct membership functions and fuzzy rules throughout the clustering process. This study analyzed 148 different data sets. Cholesterol, random glucose, systolic, and diastolic blood pressure are all included in the data collection. This learning process was conducted using a hybrid algorithm. The consequent parameters are adjusted forward using the least-square approach, while the premise parameters are adjusted backward using the gradient-descent process. The performance of a system is determined by the following indicators: accuracy, sensitivity, specification, precision, area under the curve (AUC), and root mean squared error (RMSE). The results of the training prove that ANFIS is an "excellent classification" classifier. ANFIS has proven to have very good stability across the six performance parameters. The adaptive properties used in ANFIS training and the implementation of fuzzy subtractive clustering strongly support this stability.

Corresponding Author:

Sri Kusumadewi
Department of Informatics, Faculty of Industrial Technology, Universitas Islam Indonesia
Km. 14 Kaliurang Street, Yogyakarta, Indonesia
Email: sri.kusumadewi@uii.ac.id

1. INTRODUCTION

Complications are changes or effects in a disease that result in several diseases attacking a person's body. Complications occur due to several factors. High glucose, high cholesterol, and high blood pressure are disorders that can trigger complications such as hypertension, diabetes mellitus, chronic kidney disease, and cardiovascular disorders [1]–[4]. Early preventative efforts are needed, especially for individuals who are at risk, given the severity of the issues that are predicted to occur. A system that can predict the risk of complications for someone with specified levels of cholesterol, glucose, and blood pressure is needed to anticipate this risk more quickly and accurately. These three items were chosen because they are frequently measured in clinics or when a certain institution provides free health care. These three items can also be measured independently using simple and inexpensive measurement devices. The implementation of data mining for the prediction of metabolic syndrome has been widely carried out as in [5]–[8] but data mining for the prediction of disease complications due to metabolic syndrome has not been widely applied.

The fuzzy system has proven to be reliable for solving prediction problems, especially for problems that contain uncertainty. Fuzzy inference systems (FIS) in various methods such as Tsukamoto, Takagi

Sugeno Kang (TSK), and Mamdani have been implemented in various medical cases. The advantage of FIS is the use of a rule base as knowledge that can be adopted from various experts or trusted sources. We can use the knowledge that is represented by natural language and then do the engineering of knowledge into fuzzy rules. Various conditions of a fuzzy variable can also be accommodated in various membership functions. One of the biggest obstacles in creating membership functions is determining the parameters of the membership function. For some variables in medical cases that already have certain measurement guidelines, membership function parameters can be determined based on these guidelines. There are many ways to make a membership function that is more objective. For example, we can use the data that we already have to make a membership function that can be more objective.

Although the existing knowledge in an FIS can be obtained from various sources, it does not necessarily guarantee that the knowledge possessed is complete. Incomplete knowledge is one source of uncertainty. Therefore, it is necessary to collect as much complete knowledge as possible so that the system being built has high credibility. If we already have a set of data, then knowledge in the form of IF - THEN rules can be generated from the data by using certain learning methods.

Studies on the performance of hybrid methods between neural networks and fuzzy systems in the medical field have been carried out by several researchers. Some studies are in the medical image domain, such as in [9]–[14]. The adaptive neuro fuzzy inference system (ANFIS) is a popular soft computing method. This method is also a hybrid system between fuzzy systems and artificial neural networks. ANFIS has been proven to perform well in several medical applications such as anti-cancer drugs [15], brain tumor detection [16], cancer gene recognition [17], diagnosis systems for diabetes [18], long-term prediction of blood pressure time series [19], classification of retinal images by glaucoma [20]. The ANFIS mostly uses fuzzy c-means (FCM) or Grid Partition to generate membership functions in FIS. The cluster centers resulting from the clustering of data sets are used for initializing the membership function parameters [21]. If this method is used, information on the number of clusters to be formed is required. For highly varied data, determining the number of clusters will also cause problems. Of course, medical data with various measurement results is less relevant when using this method. Pure unsupervised clustering methods are needed for this purpose. Fuzzy subtractive clustering is one way to solve fuzzy clustering problems that has worked well.

This study aims to predict the possibility of disease complications for a person based on the results of measurements of total cholesterol, random glucose, and blood pressure. Prediction is done using the ANFIS method. Fuzzy subtractive clustering is used to build a membership function in FIS. Furthermore, the performance of ANFIS will be compared with the performance of three other learning methods, namely random forest (RF), decision tree (C4.5), and naïve Bayesian classification (NBC).

2. LEARNING ALGORITHMS

2.1. Adaptive neuro fuzzy inference system (ANFIS)

The ANFIS, or adaptive network-based fuzzy inference system, is a powerful machine learning technique that uses a training algorithm to adjust the parameters of the system in order to approximate the problem under consideration [22]. ANFIS is a very accurate model, indicated by a fairly large degree of interpretation [23], [24]. This architecture is functionally equivalent to Sugeno's fuzzy rule base model. This architecture is related to a neural network with radial functions and some constraints. To make improvements to the rules, ANFIS uses a learning algorithm on a set of training data. During the learning process, the rules will adapt. To be equivalent to a fuzzy rule-based Sugeno order 1 model, a network with a radial basis function must satisfy the following conditions: (i) All outputs must be produced using the same aggregation approach (weighted average or weighted sum). (ii) The number of activation functions must be equal to or greater than the number of fuzzy rules (IF–THEN). Three (iii): If the rule base has a lot of inputs, each activation function must be the same as the membership function of the input that it is linked to.

The ANFIS network consists of the following layers [25]:

a) The first layer (input mf layer) contains neurons that represent membership functions. The parameters of an activation function can be adjusted by each neuron in this layer. Each neuron produces a membership value as its output, and the Gauss function is used to formulate this value,

$$\mu_A(x) = e^{\frac{-(x-c)^2}{2\sigma^2}} \tag{1}$$

where $\mu_A(x)$ is the membership value of x in the set A, c is the cluster center, and σ is standard deviation. c and σ are referred to as "*premise parameters".*

b) The second layer (rule layer) contains the fuzzy rules. Each neuron in this layer represents an implication function (IF–THEN rule). Typically, the "and" operator is used in every fuzzy rule. Each neuron generates the fire strength (α_i) of each rule.

c) The third layer is the normalization layer. In this layer, each neuron makes a ratio of the fire strengths of a rule to the sum of all the fire strength:

$$\overline{\propto}_i = \frac{\propto_i}{\sum_{j=1}^{n} \propto_j}, n = number\ of\ rules \tag{2}$$

The outcome is referred to as normalized firing strength.

d) The fourth layer (output mf layer) contains neurons that are adaptive to an output:

$$z_i = \overline{\propto}_i\ f_i = \overline{\propto}_i\ \left(\sum_{j=1}^{m} (p_{ij} x_j) + q_i\right) \tag{3}$$

where $\overline{\propto}_i$ is normalized firing strength in the 3rd layer, p_{ij} is the parameter of the j-th variable in the i-th rule, and q_i is constant in the i-th rule. p_{ij} and q_i are called consequent parameters. They will be adjusted to get the smallest error.

e) The fifth layer is the output layer. If the model being built has only one output variable, the neurons in this layer will calculate the final value:

$$y = \sum_{i=1}^{n} z_i \tag{4}$$

ANFIS learning can implement backpropagation or hybrid algorithms. The hybrid learning technique is an efficient parameter setting method for ANFIS [25]. In the hybrid algorithm, given the premise parameters, the output is a linear combination of the consequent parameters. The hybrid algorithm will adjust the p_{ij} and q_i parameters forward and adjust the c_{ij} and σ_{ij} parameters backward. In the forward step, the network input will propagate forward to the fourth layer, where the p_{ij} and q_i parameters will be identified using the least-square method, whereas in the backward step, the signal error will propagate backward and the c_{ij} and σ_{ij} parameters will be corrected using the gradient-descent method. Then the recursive least square estimator (LSE) is used to calculate linear parameters (p_{ij} and q_i).

Hybrid learning algorithm is based on gradient descent with adaptive learning rate. During the learning process on standard gradient descent, the learning rate will always be constant. If the learning rate is too high, the algorithm becomes unstable. On the other hand, if the learning rate is too small, the algorithm will take a very long time to reach convergence. It will be very difficult to determine what the optimal learning rate is before the training process. In fact, this optimal learning rate value will continue to change during the training process along with changes in the value of the performance function. In gradient descent with adaptive learning rate, the learning rate value will be changed during the training process to keep the algorithm stable throughout the training process. In the gradient descent algorithm with adaptive learning rate, if the learning error exceeds the previous learning error, the learning rate will be reduced by multiplying it by lr_dec. Preferably, if the learning error is smaller than the previous learning error, the learning rate will be increased by multiplying it by lr_inc. The learning process continues until it reaches the maximum number of epochs (max_epoch) or the error is smaller than the error goal.

2.2. Random forest

The principle of a random forest is to divide and conquer, meaning that a random forest will divide the predictor space into several samples, then build a random tree hypothesis on each subspace and end by averaging these hypotheses together [26]. Apart from having high predictive performance, random forest has the advantage of being an intuitive algorithm in its construction, so that it can be used by even less experienced users [27]. The formation of a random forest can be started with a basic learner in the form of a decision tree. The learning process is carried out to reduce variance. An additional element of randomness will be injected during the construction of the decision tree so that they are not too correlated with each other [26], [28]. At the same time, because the basic learner is a decision tree, there are not many assumptions about the shape of the target function that result in low bias [26]. Bootstrap is used in Random Forest to reduce decision tree bias and break splits in each decision tree.

2.3. J48 algorithm

The J48 algorithm is a derivative algorithm from The C4.5 which is implemented in Weka. Numerous additional features, including missing value accounting, decision tree pruning, continuous attribute value ranges, and rule derivation, are included in the J48 version of the C4.5 approach. Similar to the ID3 algorithm, this approach builds decision trees from a collection of training data using information entropy concept. The training data is a set $S = \{s_1, s_2, \ldots\}$ of samples that have already been categorized. Each sample s_i is represented by a p-dimensional vector (x_1, i, x_2, i, x_p, i) where x_j reflects the relevant sample's attribute values or characteristics, as well as the class to which the sample belongs. The attribute with the most information is the one to divide on in order to achieve the maximum classification accuracy. The J48 adaptively selected the data characteristic at each node of the tree that divides its collection of samples into subsets that are enriched in one or more classes most effectively. The splitting criterion is the normalized information gain, which is determined by the entropy difference. The decision is made based on the attribute with the greatest normalized information gain. The J48 algorithm then use a divide-and-conquer approach to iteratively traverse the partitioned sub lists to produce a greedy decision tree.

2.4. Naïve Bayesian classification (NBC)

NBC is an efficient and simple classifier among Bayesian classifiers. It takes the category node as the root node, its attribute nodes are mutually independent, and all attribute nodes take the category node as the father node [29]. If the training sample set is divided into k categories as C = {C_1, …, C_k} then each transcendent probability of C_i is $p(C_i)$, i = 1, …, k, the sample number corresponding to the C_i's value divides the training sample set sample number n. If there is a new sample d, the conditional probability of the C_i's is $p(d|C_i)$. The C_i's posterior probability, according to the Bayesian theorem, is $p(C_i|d) = \frac{p(d|C_i)p(C_i)}{p(d)}$. P(d) is constant to all categories, so posterior probability can be simplified as $p(C_i|d) \propto p(d|C_i)p(C_i)$.

3. METHOD

This research was completed in five stages, as shown in Figure 1. There are processes for preparing network architecture, learning, testing, and performance analysis. Each stage is described.

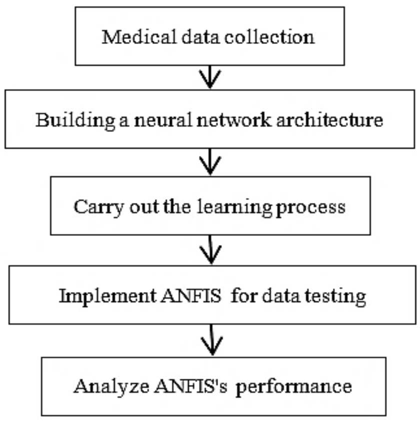

Figure 1. Research stages

Stage 1: Medical data collection

This study used 148 data sets. The data set includes cholesterol, random glucose, systolic blood pressure, and diastolic blood pressure. Data sets are taken from medical records in hospitals and data collection by health care provider partners. The data sample required is at least 40 years old. This sample consisted of 50 males and 98 females. Of the 148 samples, 94 people tested positive for complications, and 54 people tested negative for complications. Samples who were declared positive for these complications had at least suffered from hypertension, diabetes mellitus, cardiovascular disease, stroke, or chronic kidney disease. The lower limit and upper limit of each item are shown in Table 1. A total of 148 data sets will be divided into training data and testing data. The composition of training data and testing data is 80%-20%, 70%-30%, 60%-40%, and 50%-50%, respectively.

Table 1. Lower limit and upper limit of each item

Item	Lower bound	Upper bound
Cholesterol	60	387
Random glucose	69	457
Systolic blood pressure	93	210
Diastolic blood pressure	50	127

Stage 2: Developing a neural network architecture

The developed ANFIS architecture consists of five layers, namely the input membership function layer (input mf), the rule layer, the normalization layer, the output mf layer, and the output layer. The membership function of the fuzzy sets on each input variable is represented by neurons in the input mf layer. In each fuzzy set, the Gauss function is utilized as a membership function. Fuzzy subtractive clustering is used to create the fuzzy set. The rule layer contains neurons that represent fuzzy rules. The normalization layer contains the fire strength normalization results for each fuzzy rule. The mf output layer contains the neurons that will produce the output of each rule. This output is calculated using the first order Takagi Sugeno Kang (TSK) inference method. The output layer contains one neuron for complication prediction. The output of this neuron is either one (1) or zero (0). A number of 1 means that there are likely to be problems, while a number of 0 means that there are likely to be no problems.

Stage 3: Carry out the learning process

ANFIS learning is implemented on the training data in these 4 scenarios. The hybrid method is used for this learning process. The improvement of consequent parameters (p_{ij} and q_i) is carried out forward using the least-square method, and the improvement of premise parameters (c_{ij} and σ_{ij}) is carried out backward using the gradient-descent algorithm. At the end of the learning process, the neuron weights are already in a stable state. Technically, Matlab R2021a software is used as a tool in this learning process.

Stage 4: Implement ANFIS for data testing

After going through the learning process, ANFIS was tested on data testing. We use four data testing scenarios. The output of this system will be compared with the real conditions in the data set. Thus, the results from ANFIS and real conditions can be compared.

Stage 5: Analyze ANFIS's performance

ANFIS performance is assessed based on the results of the evaluation of the testing data in the data training. Performance is measured by calculating the values of six performance indicators, namely accuracy, sensitivity, specification, precision, area under the curve (AUC) on the receiver operating characteristic (ROC) curve and root mean square error (RMSE). These six indicators are also implemented in the RF, C4.5, and NBC methods. Weka 3.8.5 software is used as a tool in the learning and testing process for the three methods. It is used to look at how ANFIS compares to the three other methods.

4. RESULTS AND DISCUSSION

There are four input variables in this neural network, namely cholesterol (x_1), random glucose (x_2), systolic blood pressure (x_3), and diastolic blood pressure (x_4). The ANFIS architecture, which consists of five layers, can be seen in Figure 2. In the first layer, the membership function of each fuzzy set is formed using fuzzy subtractive clustering. The clustering process on the training data is associated with the following parameter values: (i) Maximum distance (radius) between cluster center and cluster members is 0.5; (ii) Squash factor (density reducing factor) is 1.25; (iii) The minimum value of the data point density ratio at which a candidate for a new cluster center may be considered (accept ratio) is equal to 0.5; (4) The maximum value of the data point density ratio at which a candidate for a new cluster center may be rejected (reject ratio) is 0.15.

The radius is set at 0.5. This means that the maximum distance allowed between each cluster member and the cluster center is 0.5. Thus, each cluster will have a relatively homogeneous average distance between all cluster members and the cluster center, so that the disparity in the characteristics of cluster members can be minimized. This, of course, will be different from semi-supervised fuzzy clustering such as FCM.

The results of clustering are several clusters, cluster centers (c), and standard deviations (σ), which will be the parameters of the Gauss function. The clustering process generates five clusters for each fuzzy variable, namely clusters C11 to C15 for the x_1, clusters C21 to C25 for the x_2, clusters C31 to C35 for the x_4, and clusters C41 to C45 for the x_4. Thus, the number of fuzzy sets in each variable is also equal to five and the number of rules in the second layer is also equal to five. The five rules are shown,

R1 : IF x_1 is in C11 and x_2 is in C21 and x_3 is in C31 and x_4 is in C41 and x_5 is in C51
THEN y is Out1

R2 : IF x_1 is in C12 and x_2 is in C22 and x_3 is in C32 and x_4 is in C42 and x_5 is in C52
THEN y is Out2

R3 : IF x_1 is in C13 and x_2 is in C23 and x_3 is in C33 and x_4 is in C43 and x_5 is in C53
THEN y is Out3

R4 : IF x_1 is in C14 and x_2 is in C24 and x_3 is in C34 and x_4 is in C44 and x_5 is in C54
THEN y is Out4

R5 : IF x_1 is in C15 and x_2 is in C25 and x_3 is in C35 and x_4 is in C45 and x_5 is in C55
THEN y is Out5

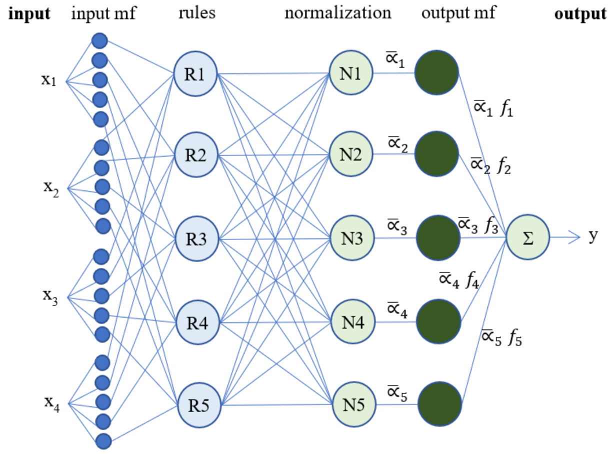

Figure 2. The ANFIS architecture

After the neural network is established, the learning process is initiated by configuring the following parameters: training epoch number (max_epoch) =20, initial step size (lr_int) =0.01, step size decrease rate (lr_dec) =0.9, step size increase rate (lr_inc) =1.1, and training error goal (eps) =0. At the end of the learning process, the premise parameters values (c_{ij} and σ_{ij}) can be seen in Table 2, and the consequent parameters values (p_{ij} and q_i) can be seen in Table 3. The standard deviation values for x_1 and x_2 in each cluster are quite high. This shows that the testing data is very diverse, especially on cholesterol and random glucose. This is one of the reasons why a fuzzy system is needed.

Table 2. Final premise parameters

	Variables	c	σ
x_1	Total cholesterol		
	Cluster 1 (C11)	190	57.69
	Cluster 2 (C12)	112	57.79
	Cluster 3 (C13)	151	57.85
	Cluster 4 (C14)	188	57.90
	Cluster 5 (C15)	261	57.82
x_2	Random glucose		
	Cluster 1 (C21)	133	68.62
	Cluster 2 (C22)	115	68.54
	Cluster 3 (C23)	153	68.57
	Cluster 4 (C24)	139	68.55
	Cluster 5 (C25)	272	68.61
x_3	Systolic blood pressure		
	Cluster 1 (C31)	138	20.56
	Cluster 2 (C32)	130	20.65
	Cluster 3 (C33)	178	20.51
	Cluster 4 (C34)	100	21.03
	Cluster 5 (C35)	120	20.73
x_4	Diastolic blood pressure		
	Cluster 1 (C41)	84	13.19
	Cluster 2 (C42)	85	13.44
	Cluster 3 (C43)	98	13.57
	Cluster 4 (C44)	60	14.05
	Cluster 5 (C45)	80	13.65

Table 3. Final consequent parameters

Output	Parameters				Constant
	p_1	p_2	p_3	p_4	(q)
Out1	-0.002317	-0,000061	-0.001851	-0.028090	4.104000
Out2	-0.001035	-0.001823	0.007803	-0.009388	-0.120600
Out3	0.002388	0.002085	0.000020	-0.013970	1.777000
Out4	0.000489	0.019520	-0.010100	0.052030	-4.167000
Out5	0.002925	0.001548	0.004948	0.004747	-1.265000

ANFIS performance is represented graphically using (ROCs) graphs for each scenario which can be seen in Figure 3. Each is Figure 3(a). ROC curve for Scenario 1, Figure 3(b). ROC curve for Scenario 2, Figure 3(c). ROC curve for Scenario 3, and Figure 3(d). ROC curve for Scenario 4. Furthermore, the performance of ANFIS is compared with that of the RF, C4.5, and NBC methods. Performance indicators include accuracy, sensitivity, specificity, precision, AUC, and RMSE. The results of each performance indicator in each method can be seen in Figures 4.

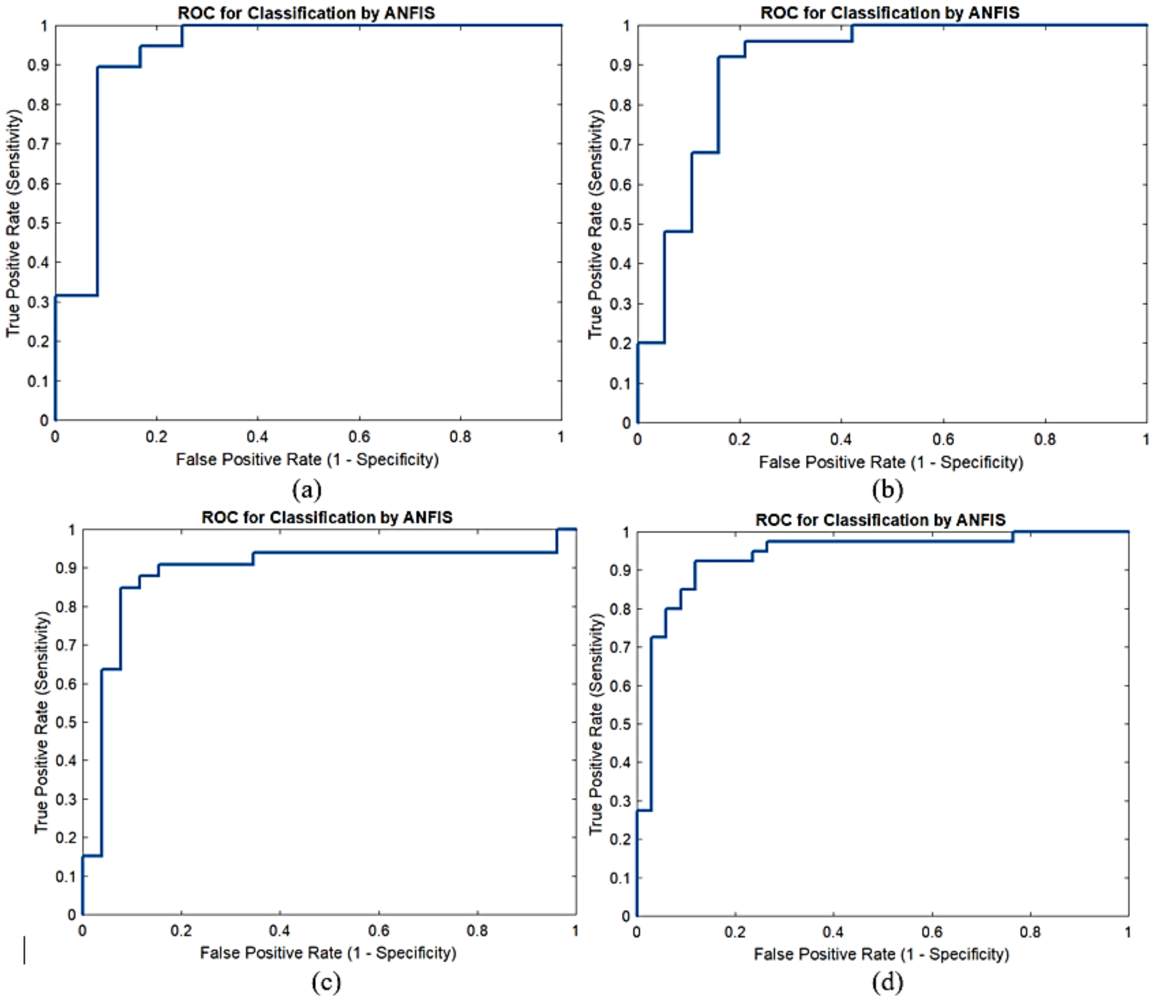

Figure 3. ROC: (a) Scenario 1; (b) Scenario 2; (c) Scenario 3; and (d) Scenario 4

Figures 4 shows comparison of performance between ANFIS and other methods (RF, C4.5, and NBC). ANFIS has a stable accuracy value well above 86% as shown in Figure 4(a). Reducing the amount of training data does not cause a decrease in ANFIS accuracy. In other words, ANFIS is stable when compared to other methods. A similar condition occurs in the NBC method. This method is also relatively stable, although the performance is not as good as ANFIS. Different conditions are shown on RF and C4.5. Both of these methods have high accuracy when implemented on 80% of the training data. However, it drops drastically, which is around 13% for RF and 22% for C4.5, when the training data is 70%.

ANFIS has a stable sensitivity value well above 0.85 as shown in Figure 4(b). Reducing the amount of training data did not cause a significant decrease in ANFIS sensitivity. Almost the same condition occurs in the NBC method. The sensitivity of this method is also relatively stable. Different conditions are shown on RF and C4.5. Both of these methods have high sensitivity when implemented on 80% of the training data. However, it drops drastically, which is around 0.25 for RF and 0.44 for C4.5, when the training data is 70%. The sensitivity level of these two methods increased drastically when they were implemented on 50% of the training data.

ANFIS has a stable specificity value well above 0.75 as shown in Figure 4(c). The greatest specificity was obtained at 50% of the training data, which was 0.912, so the specificity range for ANFIS is 0.122. Almost the same condition occurs in the NBC method. The specificity of this method is also relatively stable, although the specificity range is greater than that of ANFIS, which is 0.221. Different conditions are shown on RF and C4.5. Both of these methods have high sensitivity when implemented on 80% of the training data. However, it will continue to decrease significantly along with the decrease in the amount of training data.

ANFIS has a stable precision value well above 0.85 as shown in Figure 4(d). The range of precision values for ANFIS is 0.062. On the other hand, the NBC, RF, and C4.5 methods have different conditions. The NBC method has a fairly large range of values, namely 0.229, with the smallest precision on 70% of the training data and the largest precision on 50% of the training data. Meanwhile, both the RF and C4.5 methods have high precision when implemented in 80% of the training data and will gradually decrease to 50% of the training data.

The four methods have an AUC greater than 0.8 as shown in Figure 4(e). This means that the four methods are in the "excellent classification" category. However, when compared to the RF and C4.5 methods, both the ANFIS and NBC methods have relatively more stable AUC performance above 0.88. In the training process, the RMSE value generated by ANFIS was relatively stable in the range of 0.308 to 0.343 as shown in Figure 4(f). In the C4.5 method, the RMSE value looks very small, namely 0.2 in 80% of the training data, but it increases significantly in 70% and 60% of the training data. So, when viewed from the RMSE, ANFIS also has the best stability.

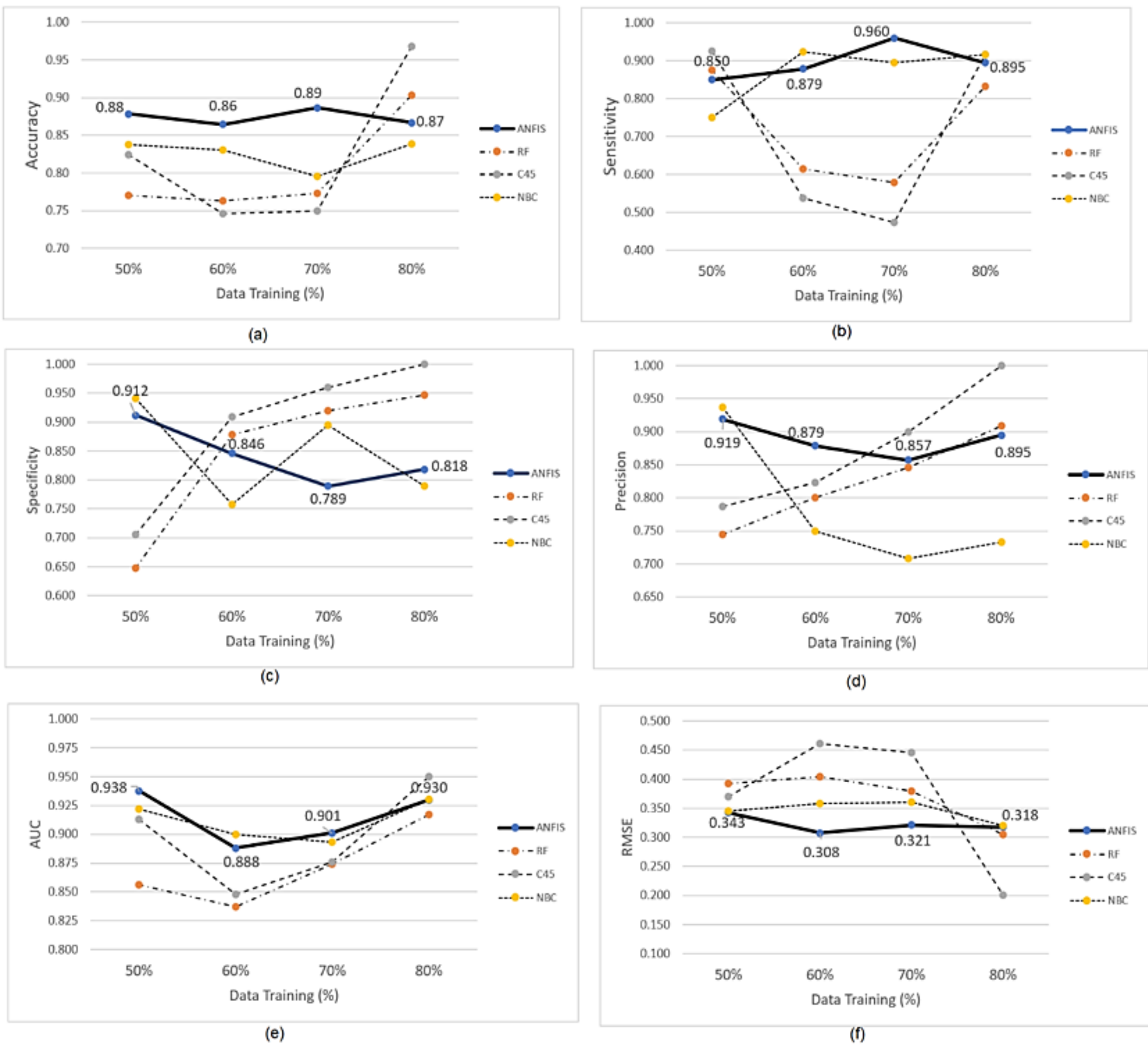

Figure 4. Comparison of performance between ANFIS and other methods: (a) accuracy; (b) sensitivity; (c) specificity; (d) precision; (e) AUC; and (d) RMSE

Table 4 shows the standard deviation for each performance parameter. It can be seen that ANFIS has the smallest standard deviation of all performance parameters other than AUC. This indicates that ANFIS has very good stability as a classifier. This stability is strongly influenced by the adaptive concept of ANFIS. The generated rules will adjust to the trained data. Likewise, fuzzy parameters as formed by membership functions and coefficients in fuzzy rules will also be adaptive to the trained data, so that regardless of the trained data, the information obtained from the trained data will be captured properly.

Table 4. Standard deviation of each performance parameter

Method	Performance Parameter					
	Accuracy	Sensitivity	Specificity	Precision	AUC	RMSE
ANFIS	0.010	0.047	0.052	0.026	0.023	0.015
RF	0.067	0.150	0.137	0.070	0.034	0.045
C4.5	0.104	0.241	0.131	0.094	0.044	0.119
NBC	0.020	0.082	0.107	0.105	0.018	0.018

High accuracy in RF was also shown in the study [30] when compared to decision tree and NBC, but in that study, it was not compared to ANFIS. The neural network used in this research is Perceptron, and it is proven that RF has higher accuracy when compared to Perceptron. In the study [31], a neural network with two hidden layers was shown to have better accuracy when compared to RF. In the study [32], neural networks were shown to have better accuracy when compared to support vector machines (SVM). The same condition is shown in the study [33], where the neural network has the best accuracy when compared to SVM and Bayesian networks. Thus, the research that we have done has actually been supported by these studies. One of the algorithms that combine the neural network and the fuzzy system is called ANFIS. This research supports the evidence that the application of intelligent systems for classification in the medical field is very appropriate, especially for machine learning [34]–[36].

5. CONCLUSION

The four methods, namely ANFIS, RF, C4.5, and NBC, are classifiers with the category of "excellent classification". Of the four methods, ANFIS proved to have the best training stability. The standard deviation, which is quite small in the performance parameters of accuracy, sensitivity, specification, precision, AUC, and RMSE, indicates the stability of the learning. The adaptive concept in ANFIS strongly supports the stability of the algorithm. By applying fuzzy subtractive clustering, each cluster will have an average distance between all cluster members and a relatively homogeneous cluster center. Of course, this is clearly different from semi-supervised fuzzy clustering techniques such as FCM. The current system generates a prediction regarding the presence or absence of complications. Prediction excludes the period in which these complications are expected to occur. Future work will involve developing a fuzzy system to predict when complications will occur.

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BIOGRAPHIES OF AUTHORS

Sri Kusumadewi She received the Doctor (Dr) in Computer Science from Gadjah Mada University Yogyakarta, 2008. She is currently working as lecturer in Informatics Department, Universitas Islam Indonesia (UII), Yogyakarta, Indonesia. Her research interest lies in decision support systems, especially in the domain of medical informatics. Many of her publications concentrated on clinical decision support systems, and various decision support system fields. She has also written dozens of books on the topic of fuzzy systems, medical informatics, and multi-attribute decision making. She can be contacted at email: sri.kusumadewi@uii.ac.id.

Linda Rosita She graduated from Gadjah Mada University in 2007 with a Specialist I degree in Clinical Pathology and in 2020 with a Specialist II degree in Hematology. She is currently working as lecturer in Faculty of Medicine, Universitas Islam Indonesia (UII), Yogyakarta, Indonesia. Her main research interests include clinical pathology and laboratory. She is a member of the European Hematology Association since 2021. Apart from being an academic, he is also active as a doctor at the "JIH" hospital and the PDHI Yogyakarta hospital. She can be contacted at email: linda.rosita@uii.ac.id.

Elyza Gustri Wahyuni She received the Master of Computer Science (M.Cs.) from Gadjah Mada University Yogyakarta. She is currently working as lecturer in Informatics Department, Universitas Islam Indonesia (UII), Yogyakarta, Indonesia. Her main research interests include medical informatics, decision support and intelligent systems. She can be contacted at email: elyza@uii.ac.id.