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Implementation Of Artificial Neural Network (ANN) Classification In Type 2 Diabetes Mellitus Cases

Naflah Faulina[1]

[1]Universitas Lampung, Indonesia
*corresponding author: naflahfaulinaa@gmail.com

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Abstract. Machine learning is a type of artificial intelligence that provides computers with the ability to learn from data. There are three main branches of machine learning, namely supervised machine learning, unsupervised learning, and reinforcement learning. One of the categories in supervised machine learning is classification. An example of a classification algorithm is Artificial neural networks are information processing systems that have characteristics and capabilities that are generally similar to human neural networks. A neural network consists of an arrangement of connections between neurons which is called architecture, a method for determining weights on connections which is called a training process or algorithm, and an activation function. This algorithm is used to classify type 2 diabetes mellitus patients as having complications and no complications by dividing training data and testing data, namely 70:30, to get the best results, namely multi layer (3 Hidden Layers with number of nodes/neurons= 5,4,3) .
Keywords: artificial neural network; classification; machine learning

Abstrak. Machine Learning *adalah jenis kecerdasan buatan yang memberi komputer kemampuan untuk belajar dari data. Ada tiga cabang utama pembelajaran mesin, yaitu pembelajaran mesin yang diawasi, pembelajaran tanpa pengawasan, dan pembelajaran penguatan. Salah satu kategori dalam pembelajaran mesin yang diawasi adalah klasifikasi. Contoh algoritma klasifikasi adalah Jaringan syaraf tiruan merupakan sistem pengolah informasi yang mempunyai karakteristik dan kemampuan yang umumnya mirip dengan jaringan syaraf manusia. Jaringan saraf terdiri dari susunan koneksi antar neuron yang disebut arsitektur, metode penentuan bobot koneksi yang disebut proses pelatihan atau algoritma, dan fungsi aktivasi. Algoritma ini digunakan untuk mengklasifikasikan pasien diabetes melitus tipe 2 memiliki komplikasi dan tanpa komplikasi dengan membagi data latih dan data uji yaitu 70:30, untuk mendapatkan hasil terbaik yaitu multi layer (3 Hidden Layer dengan jumlah node/neuron= 5,4,3).*
Kata Kunci*:* artificial neural network*; klasifikasi;* machine learning

INTRODUCTION

Machine learning is a method that can be used to carry out classification and predictions. The algorithm works by studying existing historical data sets so that patterns can be found to predict new data. There are three main branches in machine learning, namely supervised machine learning, unsupervised learning, and reinforcement learning. One of the categories in supervised machine learning is classification. An example of a machine learning

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classification algorithm is artificial neural networks (Budiharto, 2016).

According to Yang and Wang (2020) artificial neural networks are information processing systems that have characteristics and capabilities that are generally similar to human neural networks. A neural network consists of an arrangement of connections between neurons which is called architecture, a method for determining weights on connections which is called a training process or algorithm, and an activation function (Abdolrasol et al., 2021; Madhiarasan & Louzazni, 2022). A neural network consists of a large number of processing elements called neurons, units, cells, or nodes. Each neuron is connected to other neurons called directed communication links, with each weight associated. Weight represents the information used to solve the problem (Yang & Wang, 2020).

ANN have been applied effectively in diabetes research for classification purposes. Research has shown that ANN can help in early diagnosis and prediction of diabetes (Bukhari et al., 2021; Fakih et al., 2022). For example, in the Indian PIMA diabetes dataset, the most significant factors influencing diabetes classification were found to be “Glucose” and “BMI” levels, with an accuracy of 84% using a fully connected neural network. Additionally, ANN has been used in Diabetic Retinopathy (DR) stage classification, where deep learning convolutional neural networks (DLCNN) have demonstrated superior performance compared to traditional methods, achieving better classification results for DR grades using optimal features selected through Linear Discriminant Analysis (LDA) (Chaves & Marques, 2021; Pekel Özmen & Özcan, 2020). Furthermore, ANN has been used in detecting pre-diabetic conditions, showing a high accuracy rate of 99.31% in predicting pre-diabetes mellitus, thereby enabling early warning for individuals at risk of developing diabetes (Anggoro & Novitaningrum, 2021).

In real world cases, diabetes can cause complications for sufferers, so early detection is needed to treat complications in type 2 diabetes mellitus. Complications of diabetes can be fatal as they cause other diseases or organ damage, such as blood vessel damage (angiopathy)(Ling et al., 2020; Yin et al., 2024). Diabetic retinopathy, which damages blood vessels in the eyes, can lead to vision problems and even blindness, while diabetic neuropathy causes nerve damage in the feet and hands, resulting in numbness, tingling, and hard-to-resolve infections. Additionally, diabetic nephropathy can damage the kidneys and lead to kidney failure, and individuals with diabetes are at higher risk of coronary heart disease and stroke. So we need an application that can help the public in detecting complications of type 2 diabetes mellitus, namely by classifying diabetic patients with existing diabetes patient data repositories using artificial neural networks classification techniques. This study aims to obtain the results of a classification analysis of diabetes patients to differentiate between patients who experienced complications and those who did not at Mayjend HM Ryacudu Kotabumi Hospital.

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METHOD

Artificial Neural Network

Artificial neural networks are basically imitations of human neural networks. In human neural networks there are cells called neurons, likewise in artificial neural networks there is also the term neuron. Neurons in artificial neural network systems are also commonly called units, cells, or nodes. Each neuron is connected to other neurons through layers with certain weights. The weight here represents the strength of action on the chemical processes that occur in the synaptic gap. Neurons have an internal state called activation. The input to the artificial nervous system represents the synapses in the human nervous system. The Wi matrix represents dentire secretion. Meanwhile, summing in the artificial nervous system method symbolizes the addition of secretions to the human nervous system. Neural network systems are widely used in various fields including medicine, business, finance, and electronics, including signal processing and control systems (Filist et al., 2022).

Network architecture is the relationship between neurons in an artificial neural network model. Neurons or nodes are collected in a layer called a layer. The layers in the artificial neural network model are divided into three, namely:

a. Input Layer The input layer contains the initial data used as predictor variables. The units in the input layer are called input units whose job is to receive input patterns from outside that describe a problem.
b. Hidden Layer The hidden layer contains hidden units whose output values cannot be observed directly.
c. Output Layer The output layer contains units which are the result of artificial neural network model calculations. In this output layer, the classification data is obtained.

Min-Max Normalization

The backpropagation method requires data with the same range so that the output is a model that can classify the data correctly. Therefore data normalization is needed. Min-max normalization is a method that can be used to normalize data so that a data range from 0-1 is obtained. For example, data X is in the range 150 to 250, then the values will be accumulated into smaller subintervals with the range [0, 1] using the formula (Ostroumov, Marais, & Kuzmenko, 2022):

$$x\ baru = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)} \tag{1}$$

Min max normalization was chosen because according to the research A Study on Normalization Techniques for Privacy Preserving Data Mining, Min-Max Normalization has a smaller classification error rate than Z-Score and Decimal Scaling(Saranya & Manikandan, 2013).

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Backpropagation Algorithm

The backpropagation algorithm is one method that is very good in dealing with the problem of recognising complex patterns (Rani, Lakhwani, & Kumar, 2022). The backpropagation algorithm is part of the multi-layer perceptron, so a hidden layer must be used and noticed in the network structure (Kasasbeh, Aldabaybah, and Ahmad 2022). The backpropagation technique supervised learning that has a target as output by changing and adjusting the value of the weights connected to the neurons in the hidden layer. Backpropagation has two main ways of error-correction learning: forward and backward movement. In the forward movement process, the input vector is applied to the input layer in each network, which will affect all networks on a layer by-layer basis. Furthermore, the neurons are activated at this stage using the activation function (Hamad & Shehab, 2024). Then the output error or the difference between the values after being activated or the target is obtained. Then the error will be minimised by changing the weights and biases generated by moving backwards from the output previously generated. The weight of each layer in the forward movement is fixed, while in the backward movement, the weight in each layer changes based on the error correction rule (Wei et al., 2022). Here is the equation in the advanced stage:

$$Y_k = f_2[W_m + \sum_{j=1}^{p} W_{jk} \,.\, f_1[V_p + \sum_{i=1}^{n} V_{ij} X_i]] \tag{2}$$

The training process on the backpropagation includes the following steps:
The Advanced Stage The input layer will receive the initial data X_i, $i = 1,2,\dots,n$, which will be forwarded to the hidden layer, and then each node in the hidden layer Z_j, $j = 1,2,\dots,p$ will add up the weighted signals,

$$z_j = V_p + \sum_{i=1}^{n} V_{ij} X_i \tag{3}$$

use the activation function to calculate the output in the hidden layer.

$$Z_j = f_1 . z_j$$

Then the signal will be forwarded to the output layer and each node in the output layer Y_k, k = 1,2,...,m will add up the weighted signals,

$$y_k = [W_m + \sum_{j=1}^{p} W_{jk}] . Z_j \tag{4}$$

use the activation function to calculate the output in the output layer.

$$Y_k = f_2 . y_k$$

The Reverse Stage Each node in the output layer Y_k,k = 1,2,...,m will receive the pattern target corresponding to the input pattern and each hidden layer Z_j,j = 1,2,...,p will calculate δ_j They were then used to calculate the corrected weight and bias between the input and hidden layers.

$$\frac{\partial E}{\partial W} = -(t_j - Y_k) * Y_k(1 - Y_k) * X_i$$

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Modify the weight of each node in the output layer Y_k, k = 1,2,…,m will update the weight and bias values j = 1,2,…,p and each node in the hidden layer updates the weight and bias values i = 1,2,…,n so that the new weight and bias values that are obtained.

$$Bobot_{baru} = Bobot_{lama} - \eta \frac{\partial E}{\partial W} \tag{5}$$

$$Bias_{baru} = Bias_{lama} - \eta \frac{\partial E}{\partial W} \tag{6}$$

Confusion matrix

Confusion matrix, also known as error matrix, is a specific table layout and allows visualization of algorithm performance, which is usually typical of supervised learning (Saputro & Sari, 2020).

Tabel 1. Confusion matrix

Actual	Prediction	
	Positif	Negatif
Positif	TP	FP
Negatif	FN	TN

with,

1. True Positive (TP) is data that is predicted to be positive and the actual data is positive.
2. True Negative (TN) is data that is predicted to be negative and the actual data is negative.
3. False Positive (FP) is data that is predicted to be positive and the actual data is negative.
4. False Negative (FN) is data that is predicted to be negative and the actual data is positive.

Classification performance can be evaluated by paying attention to the following measures:

$$\text{Accuracy} = \frac{TP + TN}{\mathrm{TP + TN + FP + FN}} \times 100\% \tag{7}$$

$$Precision = \frac{TP}{TP + FP} \times 100\% \tag{8}$$

$$Recall = \frac{TP}{TP+FN} \times 100\% \tag{9}$$

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{10}$$

The research methodology used is Knowledge Discovery in Database (KDD). The KDD stages consist of selection, preprocessing, transformation, data mining, and interpretation/evaluation. Following are the research steps:

1. Datasets
   Data on patients who experienced diabetes complications were obtained from RSD. Major General Hm Ryacudu Kotabumi as many as 220 data.
2. Preprocessing
   The preprocessing stage is to reduce attributes that are less influential in the

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classification process. Several preprocessing stages are cleansing, case folding, tokenizing, filtering, and stemming (Pimpalkar & Raj, 2020).

3. Transformation
   The transformation stage aims to change the form of data that has been selected for the classification process in data mining (Jayasri & Aruna, 2022). The data used in the classification process must be numerical data, so it is necessary to carry out a transformation stage.
4. Data Mining
   The data mining stage is a classification process using the Artificial Neural Network algorithm with the backpropagation method (Abdelrasoul et al., 2022). The classification process consists of 2 processes, namely the training process and the testing process.
5. Interpretation/Evaluation
   This stage is to evaluate the classification performance results that have been obtained by calculating the accuracy, precision and recall values.

RESULT AND DISCUSSION

General description of research data used in the Implementation of Artificial Neural Network (ANN) Classification in Type 2 Diabetes Mellitus Cases at Major General Hm Ryacudu Kotabumi Hospital are 220 patients who underwent a health examination regarding complications of type 2 diabetes mellitus in August 2023. The patient characteristics are as follows Table 2.

Table 2. Characteristics of diabetes mellitus data

Variable	Scale	Description
Complication Status	Nominal	0 = No Complications 1= Complications
Blood Glucose Levels		mg/dL
Cholesterol Levels	Numerical	mg/dL
Serum Uric Acid Levels	Numerical	mg/dL
Triglycerides	Numerical	mg/dL
BMI	Numerical	kg/m^2
Age	Numerical	Year

Next, carry out a classification analysis of the Diabetes data using an Artificial Neural Network (ANN), then divide the testing data and training data 70:30 as follows:

$$\begin{aligned}\text{Training} &= \text{Proportion of training data} \times N \\ &= 70\% \times 220 \\ &= 154\end{aligned}$$

$$\begin{aligned}\text{Training} &= \text{Proportion of testing data} \times N \\ &= 30\% \times 220 \\ &= 66\end{aligned}$$

The next step is to create a single layer with nodes of 5 and a multi layer with nodes of (5,4) and (5,4,3). The research results can be seen as follows:

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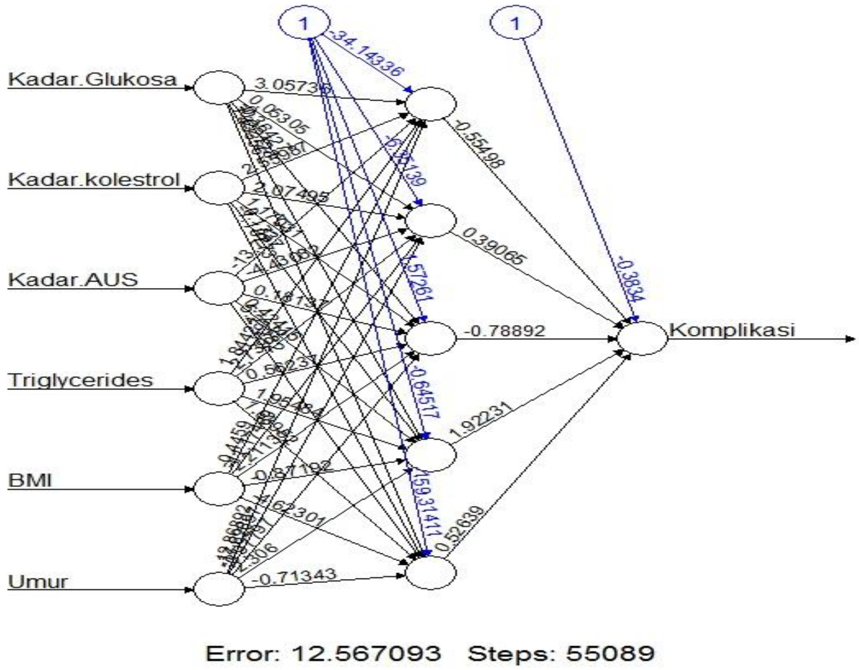

Figure 1. Single Layer

In the plot Figure 1. it is known that this network has 6 inputs which represent 6 independent variables, where each input node represents a variable. Because we are making an ANN with a single layer, there is only 1 hidden layer which has 5 neurons. Then the black lines connecting each neuron are synapses which have weights and the blue lines show the bias value. Then the information below the plot is in the form of Error and Steps values, where the error value is the loss value obtained when carrying out training on this network, then the error value is 12.567093 while the steps value is the number of iterations carried out by the machine, in the picture above it is obtained that the machine has carried out 55089 iterations to produce the weight shown in the black lines.

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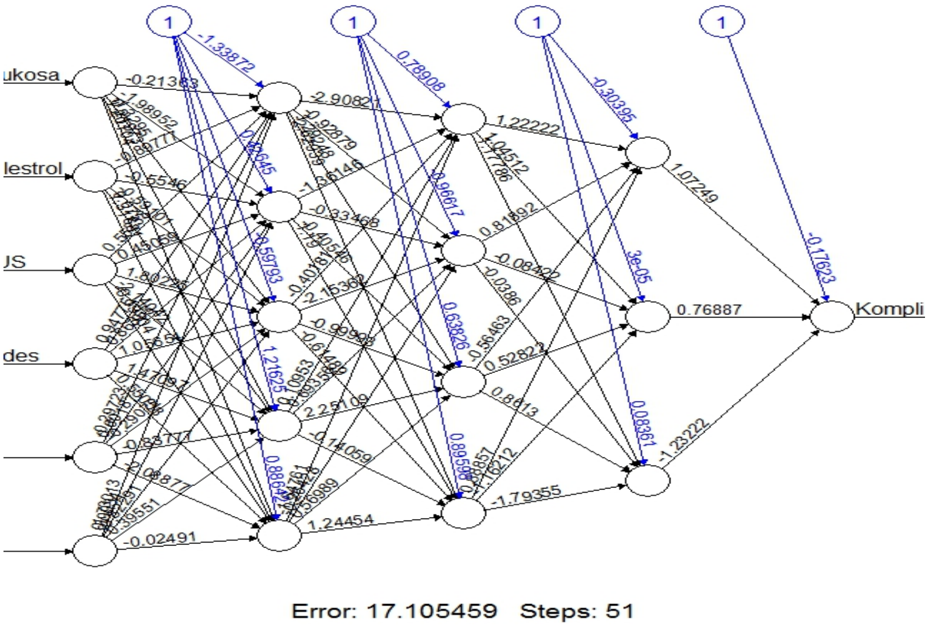

Figure 2. Multi Layer

In the plot Figure 2. it is known that this network has 6 inputs which represent 6 independent variables, where each input node represents a variable. Because we are making an ANN with multiple layers, there are 3 hidden layers, where the first layer has 5 nodes/neurons, the second layer has 4 nodes/neurons, and the third layer has 3 nodes/neurons. Then the black lines connecting each neuron are synapses which have their respective weights and the blue lines show the bias value.

Then the information below the plot is in the form of Error and Steps values, where the error value is the loss value obtained when we carry out training on this network, here the error value is 17.105459 while the steps value is the number of iterations carried out by the machine, in the picture above, it can be seen that the machine has carried out 51 iterations to produce the weights shown in the black lines. The results of the classification performance evaluation based on a 70:30 comparison of training and testing data with single layer and multi layer are as follows Table 3.

Table 3. Confusion Matrix Single Layer

Actual Class	Prediction Class	
	No Complications	Complications
No Complications	34	3
Complications	24	5

From Table 3. the TP values or those that were correctly predicted as no complications were 34, FP or those that were actually predicted to be no complications but were predicted to be complications were 3, FN or those that were correctly predicted as complications but

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were predicted to be no complications were 24, and TN or those that were correctly predicted as comments on complications. as many as 5. So the precision, recall, f1-score and accuracy values can be seen as follows.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100\% = \frac{34 + 5}{34 + 5 + 3 + 24} \times 100\% = 59\ \%$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100\% = \frac{34}{34 + 3} \times 100\% = 90\ \%$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\% = \frac{34}{34 + 24} \times 100\% = 58\%$$

$$\text{F1} - \text{score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} = 2 \times \frac{0{,}90 \times 0{,}58}{0{,}90 + 0{,}58} = 70\%$$

Table 4. Confusion matrix Multi Layer layer

Actual Class	Prediction Class	
	No Complications	Complications
No Complications	45	19
Complications	0	2

From table 4, the TP values or those that were correctly predicted as no complications were 45, FP or those that were actually predicted to be no complications but were predicted to be complications were 19, FN or those that were correctly predicted as complications but were predicted to be no complications were 0, and TN or those that were correctly predicted as comments on complications. as many as 2. So the precision, recall, f1-score and accuracy values can be seen as follows.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100\% = \frac{45 + 2}{45 + 19 + 0 + 2} \times 100\% = 71\ \%$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100\% = \frac{45}{45 + 19} \times 100\% = 70\ \%$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\% = \frac{45}{45 + 0} \times 100\% = 100\%$$

$$\text{F1} - \text{score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} = 2 \times \frac{0{,}70 \times 1}{0{,}70 + 1} = 82\%$$

Table 5. Comparison of accuracy, precision, recall and f1-score values

	Accuracy	Precision,	Recall	F1-Score
Single Layer (1 Hidden Layer with 5 nodes/neurons)	59%	90%	58%	70%

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Multi Layer (3 Hidden Layers with number of nodes/neurons= 5,4,3)	71%	70%	100%	82%

Based on the Table 5. it shows that the multi layer results have accuracy, precision, recall and f1-score values that are greater than other data. This study utilized Artificial Neural Networks (ANN) to classify complications in type 2 diabetes mellitus based on several patient health variables. The primary findings of this research are noteworthy. The single-layer model, featuring one hidden layer with 5 neurons, achieved an accuracy of 59%. In contrast, the multi-layer model, which included three hidden layers with 5, 4, and 3 neurons respectively, achieved a higher accuracy of 71%. In terms of model performance, the single-layer model had a higher precision at 90% compared to the multi-layer model's 70%, but it exhibited a lower recall at 58% versus the multi-layer model's perfect recall of 100%. Consequently, the multi-layer model also boasted a higher F1-score of 82% compared to the single-layer model's 70%.

The strengths of this study are apparent. The use of ANN enhances the model's ability to capture complex patterns within the data, thus improving classification accuracy. Additionally, the balanced split of training and testing data (70:30) ensures effective validation of the model against unseen data. Furthermore, the multi-layer ANN architecture demonstrates improved performance metrics, particularly in accuracy and F1-score, compared to the single-layer model.

However, there are notable weaknesses. The multi-layer model is at risk of overfitting, where it learns the training data too well, potentially diminishing its performance on new testing data. Additionally, the single-layer model required significantly more iterations (55,089) compared to the multi-layer model (51), indicating potential inefficiency. Another concern is the imbalance in predicting complication classes, especially in the multi-layer model, which achieved a recall of 100% for complications, suggesting a bias towards one class.

The real-world implications of this research are significant. ANN models can be employed as tools for the early detection of diabetes complications, allowing for more timely and effective interventions. This capability enables personalized treatment plans, as doctors can identify patients at high risk of complications and tailor their care accordingly. Moreover, implementing this model in healthcare settings can enhance efficiency in managing diabetic patients, reducing the workload on medical professionals and improving overall service quality.

When compared to previous research, this study stands out. For instance, research by Ye et al. (2020), which used logistic regression, achieved an accuracy of 65%. The multi-layer ANN model in this study surpasses that with an accuracy of 71%. Similarly, a 2022 study by ABC using Random Forest achieved an accuracy of 68%, again lower than the multi-layer

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ANN model's performance. This study may be among the few that use a specific multi-layer ANN architecture with designated neuron combinations for type 2 diabetes mellitus complications, providing a novel contribution to the field.

In conclusion, this research illustrates that employing ANN, particularly with a multi-layer architecture, can significantly enhance the classification performance for complications in type 2 diabetes mellitus. Despite challenges such as potential overfitting and high iteration requirements, the model offers valuable real-world implications for early detection and personalized treatment of diabetic patients. Compared to previous studies, the multi-layer ANN model in this research shows superior performance, adding valuable insights to the field.

CONCLUSION

Based on the results of research on the classification of diabetes patients who experienced complications and those without complications at Mayjend HM Ryacudu Kotabumi Hospital using the Artificial neural networks method with a 70:30 distribution of training and testing data, good results were obtained in multi layer (3 Hidden Layers with number of nodes/neurons= 5,4,3) with a high level of accuracy seen in the confusion matrix test showing 71% accuracy value, 70% precision value, 100% recall value, and 82% F1-Score value.

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