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Optimization of Deep Neural Networks with Particle Swarm Optimization Algorithm for Liver Disease Classification

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ABSTRACT

Liver disease has affected more than one million new patients in the world. which is where the liver organ has an important role function for the body's metabolism in channeling several vital functions. Liver disease has symptoms including jaundice, abdominal pain, fatigue, nausea, vomiting, back pain, abdominal swelling, weight loss, enlarged spleen and gallbladder and has abnormalities that are very difficult to detect because the liver works as usual even though some liver functions have been damaged. Diagnosis of liver disease through Deep Neural Network classification, optimizing the weight value of neural networks with the Particle Swarm Optimization algorithm. The results of optimizing the PSO weight value get the best accuracy of 92.97% of the Hepatitis dataset, 79.21%, Hepatitis 91.89%, and Hepatocellular 92.97% which is greater than just using a Deep Neural Network.

Keywords*:* Particle Swarm Optimization, Deep Neural Networks, Classification Diease Liver

1. INTRODUCTION

The liver is one of the largest organs in the human body, playing a major role in metabolism and serving several vital functions, the liver is located in the right abdomen below the diaphragm [1], [2]. The liver produces hormones and proteins, controls blood sugar, and helps control blood clotting. The liver is a major health problem worldwide, with more than one million new patients diagnosed with the disease [3]. There are many types of liver disease problems that result in liver disorders, such as Wilson's disease, hepatitis, liver cancer, and cirrhosis [4].

Indications of liver disease include jaundice, abdominal pain, fatigue, nausea, vomiting, back pain, abdominal swelling, weight loss, and enlarged spleen and gallbladder. Furthermore, certain abnormalities of the liver are very difficult to recognize in the early stages of diagnosis because the liver functions normally even though some functions are damaged[5]. This causes patients to often fail to detect the disease. Therefore accurate early detection is necessary so that the medication and treatment required by the patient can be done correctly.

Liver disease detection has been done by research using data mining techniques in the medical field, to diagnose liver disease with classification algorithms in data mining[2]. Using Random Forest and Artificial Neural Networks models by proposing a 10-fold cross-validation technique and tuning parameters resulted in the best accuracy in Artificial Neural Networks with an accuracy value of 85.29%, and a positive predictive value of 89.47%, and a sensitivity of 80%[6].

Meanwhile, there is a Liver cancer classification carried out using the Deep Neural Network model which is optimized by adding 3 different activation functions, namely the Min-Max, Sigmoid, and Softmax, and the addition of batch normalization to each hidden layer in the DNN architecture resulting in the best value in the ReLU activation function with Min-Max data normalization which produces an accuracy of 98.33% and uses parameters 2 hidden layers, learning rate 0.04 and 200 epochs[7]). From the related research that has been described regarding the classification of liver disease, it still uses a standard algorithm model such as in ANN determining weights randomly, selecting good parameters for SVM and there is a random division of training data, testing data so that it affects the results obtained.

Compared the optimization of weighting and bias in the DNN model with Ant Colony Optimization (ACO) and compared the Artificial Neural Network (ANN) model[8]. States that weight initialization in artificial neural networks is very important to determine convergence[2]. Weight initialization has a major contribution as a significant factor in the final quality of the artificial neural network and its convergence rate[9]. Weight optimization in neural networks using the particle swarm optimization (PSO) algorithm, is used to obtain optimal solutions that have a simple concept[10].

Various background problems have been discussed, this research proposes to improve the classification performance of the Deep Neural Network (DNN) architecture, in terms of weight initialization with the Particle Swarm Optimization (PSO) algorithm in the classification of liver disease.

2. MATERIALS AND METHODS

In the proposed liver disease classification research, using the Deep Neural Networks (DNN) algorithm, the weight initialization process is carried out with a particle swarm optimization algorithm, on neural nets to get convergent weights. The process of each stage will be explained as follows:

2.1 DATA PREPARATION

The liver disease dataset is obtained from the UCI repository which uses 3 types of datasets, namely Hepatitis, Hepatocellular Virus 14 and Indian Liver Disorders. Each dataset has a preprocessing process. The following dataset explanation of the liver disease dataset is explained in the table 1.

TABLE 1.
Datasets

NO	Dataset	Attributes	Missing Value	Record
1	Hepatitis	20	Yes	155
2	Hepatocellular Virus	14	Yes	584
3	Indian Liver	10	Yes	583

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2.2 DATA PREPROCESSING

Data preprocessing is data cleaning and replacing (missing values) on datasets that contain noise data to be carried out in the next stage. Data preprocessing processes are used such as data cleaning and data transformation [11].

2.3 DEEP NEURAL NETWOKS (DNN)

Deep Neural Network is an algorithm that follows the structure of a complex artificial neural network, and consists of more than one input, hidden layers, and has an output layer.[1], [12].

Neural Networks have neurons, which are calculated from the number of inputs by adding the bias [13], [14]. The used DNN parameters are the input layer, bias, learning rate, weight and epoch. The activation function for each layers use ReLU, while the sigmoid activation function is used as the output function [1]. The proposed Deep Neural Networks architecture is shown in Figure 1.

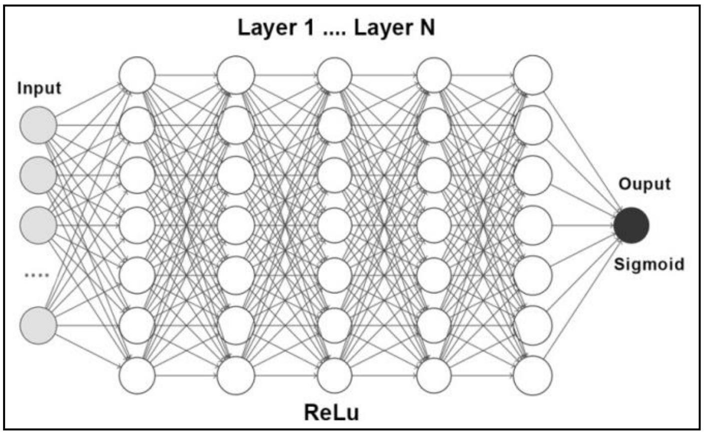

FIGURE 1. Arsitektur Deep Neural Network

Deep Neural Networks (DNN) equation in general:

$$y_i = s\ (\sum_{i=1}^{N} W_{ij} x_j +\ b_i\ ) \tag{1}$$

Meanwhile, the ReLU activation function equation is as follows:

$$R = \max\ (0, x) \tag{2}$$

$$\frac{\partial \mathrm{R}}{\partial \mathrm{x}} = \begin{cases} 1 & x > 0 \\ 0 & x \leq 0 \end{cases} \tag{3}$$

Then the Sigmoid activation function equation is as follows:

$$S = \frac{1}{1+e^{-cx}} \tag{4}$$

$$\frac{\partial \mathrm{R}}{\partial \mathrm{x}} = \frac{1}{1+e^{-cx}} \times (\ 1 - \frac{1}{1+e^{-cx}}) \tag{5}$$

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2.4 WEIGHT INITIAIZATION

In the classification process of neural networks, the initialization weight is an important step used before training the artificial neural network. The initialization weight is adjusted repeatedly while training the network. This is done until it reaches a convergent value and ideal weights are obtained [15]. In this study, weight initialization was carried out with the Meta-Heuristic Particle Swarm Optimization (PSO) algorithm.

2.4.1 PARTICLE SWARM OPTIMIZATION (PSO)

Particle Swarm Optimization (PSO) is a technique for finding global optimum solutions based on the social behavior of birds in flocks. A swarm consists of a set of particles, each particle having a potential solution. These particles fly in the dimensions of the searching space to find the best solution. The PSO algorithm can perform the optimization by moving within certain function problems. A particle movement can be influenced by the best solution (pbest) and the best solution in general from other particles (gbest) [16]. In general, the equation of the Particle Swarm Optimization algorithm is aimed at the equation below.

$$v_{k+1}^{i} = \omega * v_{\mathrm{k}}^{\mathrm{i}} + c_1 * rand * pbest^{i} - x_k^i + c_2 * rand * gbest - x_k^i \qquad (6)$$

From this equation, the best solution value will be obtained from the local best (pbest) or global best (gbest) value.

2.5 DNN CLASSIFICATION AND INITIALIZATION OF PSO WEIGHT

Classification of Deep Neural Networks is done by optimizing the initial weights using the Particle Swarm Optimization algorithm, to obtain convergent weights. The flowchart from DNN + PSO is shown in the figure 2.

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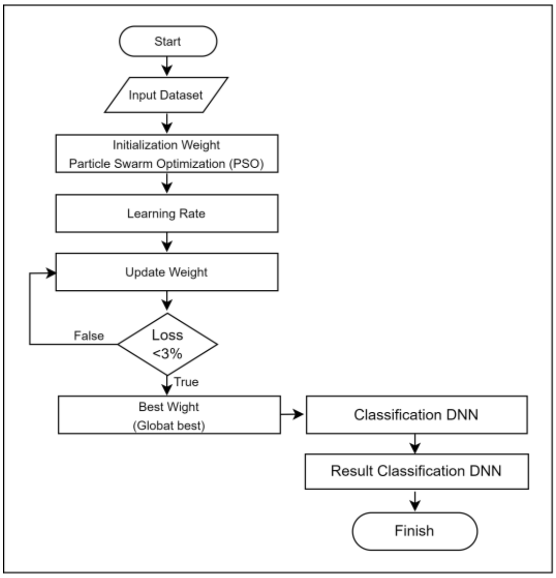


FIGURE 2. Weight Initialization of DNN + PSO

The weight initialization process with the Particle Swarm Optimization algorithm in DNN, by determining the particle value and PSO iteration randomly. Furthermore, the use of the global best optimizer function to determine the best weight that will be used during the DNN classification process. This research determines the particle value c1 = 0.4 c2 0.6 and w 0.4, for PSO iterations following the number of epochs for DNN.

3. RESULT AND DISCUSSION

Tests conducted on the Deep Neural Network (DNN) model use several measurement parameters, each layer is done as much as 1 layer, 2 layers, 3 layers, 4 layers, and 5 layers, then trained using 50 epochs, 100 epochs, 150 epochs, 200 epochs and 250 epochs on each layer. In addition, the activation function used in each layer uses the ReLU activation function, then the output activation function uses Sigmoid activation for classes 0 or 1 (binary). The optimizer function used is Adam, while the loss function uses binary and categorical cross-entropy. Furthermore, for the Particle Swarm Optimization (PSO) algorithm parameters, using the velocity parameter value c1 = 0.4 c2 = 0.6, and w = 0.4. The optimizer function used in PSO is global best and the dimension is adjusted to the total number of parameters in the Deep Neural Networks (DNN).

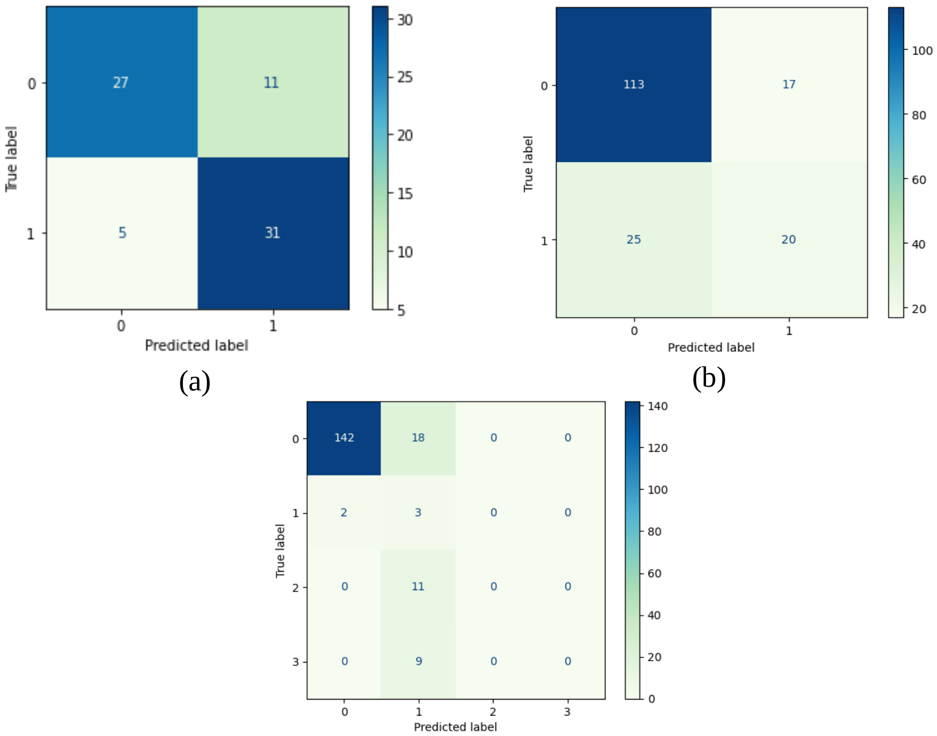
3.2 DNN CLASSIFICATION RESULTS

The results of Deep Neural Network (DNN) classification testing on hepatitis, Hepatocellular Virus, and Indian Liver datasets were carried out by testing different epochs and layers. The best results of the tests that have been carried out are in the table.

TABLE 2.
DNN Classification Results

Dataset	Parameter		Classification Report			
	Layer	Epoch	Accurasy	Precesion	Recall	F1 - Score
Hepatitis	4	250	86,49	86,00	86,00	86,00
Indian Liver	5	200	76,57	76,00	77,00	73,00
Hepatocelullar	4	50	81,62	84,00	82,00	82,00

Evaluation of the DNN model that has been carried out gets the best accuracy on the Indian Liver dataset resulting in 76.57% accuracy, while the Hepatocellular dataset displays an accuracy value of 81.62%, then the best DNN classification results from the previous results, getting an accuracy of 86.49%, precision 86.00%, recall 86.00% and F1-Score 86%. The following is the confusion matrix of each dataset Figure .



(a) (b)

(c)

FIGURE 3. (a) Confusion Matrix DNN Dataset Hepatitis; (b) Confusion Matrix DNN Dataset Indian Liver; (c) Confusion Matrix DNN Dataset Hepatocellular

3.2 DNN CLASSIFICATION RESULTS - PSO WEIGHT OPTIMIZATION

The results of Deep Neural Network (DNN) classification testing carried out weight initialization with Particle Swarm Optimization (PSO) on hepatitis, Hepatocellular Virus, and Indian Liver datasets were carried out by testing different

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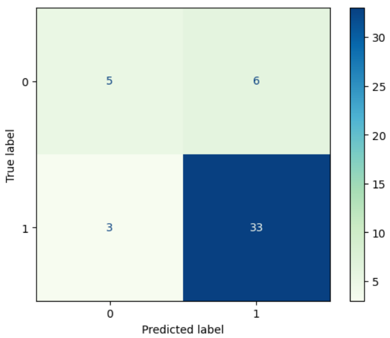
epochs and layers. The best results of the tests that have been carried out are in the table.

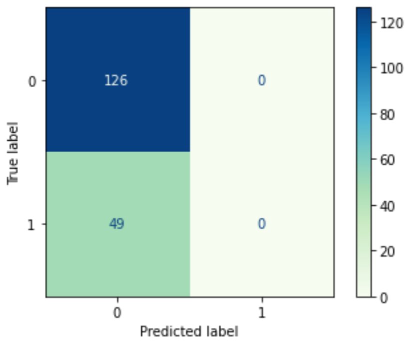
TABLE 3.
DNN + PSO Classification Result

Dataset	Parameter			Classification Report			
	Layer	Epoch	Global Best	Accurasy	Precesion	Recall	F1 - Score
Hepatitis	4	100	0,145	91,89	51,00	100,00	86,00
Indian Liver	1	200	0.284	79,21	61,00	50,00	44,00
Hepatocelullar	1	50	0,128	92,97	61,00	59,00	56,00

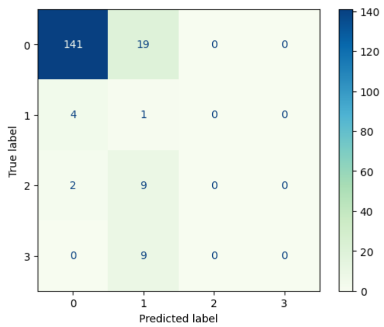
Evaluation of the DNN model that has been carried out gets the best accuracy on the Indian Liver dataset resulting in 79.21% accuracy, while the Hepatitis dataset displays an accuracy value of 91.89%, then the best DNN classification results from the previous results, getting the highest accuracy of 92.97%, precision 61.00%, recall 59.00% and F1-Score 56% on the Hepatocellular dataset. The following is an image of the confusion matrix from each dataset.



(a)



(b)



(c)

FIGURE 4. (a) Confusion Matrix DNN + PSO Dataset Hepatitis; (b) Confusion Matrix DNN + PSO Dataset Indian Liver; (c) Confusion Matrix DNN + PSO Dataset Hepatocellular

3.3 ANALYSIS OF RESEARCH RESULUT

The influence of the Particle Swarm Optimization (PSO) algorithm to initialize the weights, can affect the results of Deep Neural Networks (DNN) classification, on the classification of liver disease with a velocity parameter value of c1 = 0.4 c2 = 0.6 and w = 0.4. Then the use of the global best optimizer and the determination of the dimension value obtained from the total DNN parameters can find the best solution for determining the weight value of Deep Neural Networks (DNN). While determining the initial parameter value in the Particle Swarm Optimization (PSO) algorithm can also affect the accuracy of results in the classification of liver disease.

4. CONCLUSION

The Particle Swarm Optimization (PSO) algorithm is able to improve the accuracy of results in the Deep Neural Networks (DNN) method to train the best weight value from the results obtained in the global best PSO value. Then the DNN classification results with weight initialization with PSO, there is a Hepatocellular dataset with the highest accuracy value of 92.97%, while only using Deep Neural Networks alone obtained an accuracy of 81.62%.

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