Machine Learning: Fisher Fund Classification using Neural Network and Particle Swarm Optimization

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***Abstract*-Assistance fishery can increase the income of fishermen and contribute to the country. Required classification awarding kind of help to improve the utilization of fund. In this research the ML to learn the features in a dataset of combinations Fishermen Card database and data Monitoring and Evaluation fisheries fund. ML process performed by NN MLP models combined with PSO with performance models such as Precision qualitative reached 0.75, sensitivity is reduced to 0.44, with the quantitative achievements reached 0.66 Accuracy and Error 0.34 with network model and small parameters.**

Keywords - Fishers Fund Classification, Machine Learning, Multilayer Perceptron Neural Network, Particle Swarm Optimization

I. INTRODUCTION

Fishing is a strategic sub-sectors in development. Efforts to improve the construction was done with the fund fisheries infrastructure. Utilization can help increase the income of fishermen and contribute to state revenues [1], Utilization of fund is still low due to the provision of fund that is not targeted[2], Utilization of fisheries fund is influenced by the characteristics and motivations of fishermen in an effort to increase revenue [3], [4]. To overcome these problems required the classification of the provision of the type of fund and beneficiary fishermen to learn the facts.

Machine Learning (ML) was able to generalize the problem by studying the aspects of the relationship between variables uncertainty in problem-based on previous events [5] where ML is able to model the cognitive problems by studying the pattern of phenomena through mathematical models and render a decision based on the learning process. Classification by Neural Network (NN) on the ML has a higher classification accuracy than the other models in cognitive problems [6]. Classification using NN contribute to the organization to reduce the risk of failure against the decision with the various factors that influence analyzing [7].

Particle Swarm Optimization (PSO) is used in nonlinear problems to determine the best variable in dimension optimization problems with high performance as well as reduce up to half of the accumulation process in achieving the target computing [8]. ML process can get stuck in local optima and minima are influenced by the dynamics on the ground so that the process of generalization can be stuck in a deadlock in the process of finding the best model. To address these problems used PSO in NN training process in finding the best model to overcome the deadlock and reduce errors with better prediction compared with conventional methods [9].

In this study, the issues raised regarding the classification of utilization of fishery targeted assistance based on the characteristics and motivations of fishermen using a model obtained through the process of ML using NN combined with PSO. The challenges in this study used data that were influenced by the inadequate fund in the field in providing in fisher fund that deviated from the normal pattern and became a problem in normalizing the existing normal pattern.

II. RELATED WORK

A. Feature Dataset

Materials used in this research is Fishermen Cards data with features such as gender, fishing status, fishing gear, boat ownership, boat size, fishing competence, onboard position on the boat, marital status, status in the family, number of family members, number of dependents, level of education and Monitoring and Evaluation of Fisher Fund data in the form of joint venture group, which distributed fund packages as well as monitoring the use of fund resulting class stating whether or not the use of a support failure. And then, data will then be used in the process of ML as a dataset.

B. Research Procedure

The stage in this study conducted by adopting stages in the ML from data is a fact that happened before in the following stages:

- Selection of the characteristic features and motivation of fishermen into training dataset and testing in the learning process.
- RAW preprocessing training and testing datasets into continue numerical and categorical.
- Implementation and testing of ML using NN which use PSO training.

Of the ML will get the best model that will be used in the classification process to request the help of the fishery. Of training and testing dataset that is included in the stages of feature selection, then do preprocess to be used in the process of learning and testing. The results of the learning models are then used for testing. After the training and testing, then the next stage classification process is carried out which can be viewed as in Figure 1:

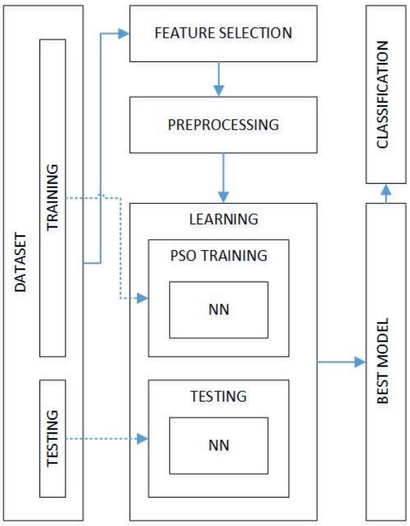

FIGURE 1. LEARNING AND CLASSIFICATION PROCEDURE

III. BACKGROUND THEORY

A. Machine Learning

Machine Learning (ML) is part of the Artificial Intelligence (AI) whereas the decision does with the learning process of the data. ML aims to make a pretty good prediction and can be used. The main classes of ML consist of supervised and unsupervised learning. Supervised learning aims for classification based on the class that has been determined, otherwise unsupervised learning aims for clustering based on similarity of the pattern [10].

ML implementation begins with the selection of feature extraction which is an influential input feature. Once it is done preprocessing of the training dataset and testing in the form of RAW data encoding.

Data encoding results and then put into learning algorithm. In this research used as model NN learning algorithms trained to use PSO to find the best model to make predictions. The achievement of these models is measured using quantitative and qualitative value in the confusion matrix based on the value of True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). It can be shown in Table 1:

TABLE I. CONFUSION MATRIX

actual	Prediction	
	True	***false***
True	TP	TN
false	FN	FP

From Table I earned achievement Precision model in the form which is the level of credibility of the data based on the process of learning. Addressing sensitivity level of inaccuracy of data input to the output class should be. Accuracy is the degree of similarity between the actual and predicted values, while the error is inversely proportional to the accuracy [6]. This can be seen through Equation 1-4:

$$Precission=\frac{TP}{TP+FP} \tag{1}$$

$$Sensitivity=\frac{TP}{TP+FN} \tag{2}$$

$$Accuracy=\frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

$$Error=\frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

B. Neural Network

Neural Network (NN) is a learning algorithm can find anomalous data, classify and then predict [11] - [13]. Multi-Layer Perceptron (MLP) is one of the architectural NN for classification consisting of nodes targeted start of input neurons (feature), hidden layers, and then output layer or better known as feedforward wherein the layers of hidden and output choosing the weight of neurons x and bias b with nodes that are connected to the input $x_i$which will be weighted to the next layer $x_{i\text{-}j}$ through the activation process f with the influence of the exponent e. For activation of the hidden neurons activation function used hypertanget $tanH$, while the output layer using softmax s activation which can be seen in Equation 5-7:

$$x_{i\text{-}j}=f\left(\sum_{i=1}^{n} x_i w_i+b\right) \tag{5}$$

$$f(x)_{tanH}=\frac{e^{2x}\text{-}1}{e^{2x}+1} \tag{6}$$

$$f(x)_s=\frac{1}{1+e^{-x}} \tag{7}$$

Results of NN form layer network model and the weights and biases best measured by the achievement of a model [6].

C. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is an evolutionary algorithm and may be stuck on local and global optima - minima. PSO uses swarm is a collection of particles, and each particle trying to find an optimal solution which is an objective fitness of the issues to be optimized through communication with another particle [14]. Fitness in the PSO is the objective function of the problem to be optimized, the general comparison of fitness on the position of the particle b and fitness on the particle's position next $b1$ in the whole of swarm i to j at iteration k is based on the particle's position globally best gBest in all iterations obtained from a collection pBest best position in a swarm of particles in each iteration *k*. The next movement of the particle positions *xi + 1* in the swarm is affected by the initial particle position *x* and velocity *v* obtained from pBest and gBest that have been found, the inertia weight w in each iteration and social constants *c1* and *c2* cognitive, along with random *r1* and *r2* [15]. This can be seen in Equation 8-13:

$$F_i^k=f\left(x_i^k\right), \forall i \text{ and } F_i^{k+1}=f\left(x_i^{k+1}\right), \forall i \tag{8}$$

$$\textbf{if}(F^{k+1}_{pBest} < F^{kl}_{pBest}) \textbf{ then } gBest^k = pBest^{k+1} \textbf{ else } gBest^k = pBest^k \tag{9}$$

$$\textit{if}(F_{b1} < F_b) \textit{ then } pBest^k_{i,j} = X^k_{b1} \textit{ else } pBest^k_{i,j} = X^k_b \tag{10}$$

$$X^{k+1}_{i,j} = X^k_{i,j} + V^{k+1}_{i,j}; \forall j \text{ and } \forall i \tag{11}$$

$$V^{k+1}_{i,j} = (w \times V^k_{i,j} + c1 \times r1 \times \left(pBest^k_{i,j} - X^k_{i,j}\right) + (c2 \times r2 \times \left(gBest^k - X^k_{i,j}\right); \forall j \text{ and } \forall i \tag{12}$$

$$w = \frac{w_{max} - k \times (w_{max} - w_{min})}{maxiter} \tag{13}$$

D. *Hybrid Neural Network (NN) and Particle Swarm Optimization (PSO)*

Hybrid NN-PSO is done by finding the weights *w* and the bias *b* best of scheme NN where the fitness function in PSO are forward-propagation of NN, convergence is obtained by gBest best of alliterations based on comparative results of the classification of neuron output and the actual class using the confusion matrix to measure the optimum performance of the ML. The learning process is done by PSO while the classification process carried out by NN [16]. Pseudocode of Hybrid NN-PSO can be seen in Figure 2:

```
Procedure NN (Input Feature, Class) : Finding Best Model
Initialize NN Schema (Number Of Hidden Layers, Neurons
and Biases)
Initialize PSO parameter (Swarm dimension (Number of
Particles), Inertia Min - Max, C1 & C2, Max of Iterations
and Convergence Condition)
Initialize Swarm Position and Velocity
while k < Max of Iterations or Convergence Condition not
Statisfied do {
   for i = 1 to Swarm(Number of Particles j) do {
      Cost Function (NN : Forward-Propagation) for find
      best Fitness b
      Generate new Velocity
      Generate new Swarm Position
      Cost Function (NN : Forward-Propagation) for find
      best Fitness b1
      Update pBest :best fitness foreach Swarm i - j in
      each iteration k
      i++
   }
   Update gBest : best fitness found in k iteration
   k++
}
Return best Particle Position (gBest) : best Fitness
```

FIGURE 2. NN - PSO PSEUDOCODE

IV. IMPLEMENTATION, RESULT AND DISCUSSION

A. *Implementation*

ML implementation begins with preprocessing features continue into numeric and categorical features can be seen in Table II:

TABLE II. FEATURE INPUT PREPROCESSING

N.	Input Features		
	name	***raw***	***encoded***
1.	Fishing Status	Word	Numeric Continue
2.	Boat ownership	Word	
3.	Boat size	Numeric	
4.	Fishing competence	Numeric	
5.	Onboard Position on the boat	Word	
6.	Number of Family members	Numeric	
7.	Number of dependents	Numeric	
8.	Level of Education	Word	
9.	Venture Group	Word	
10.	Gender	Word	Categorical
11.	Fishing Gear	Word	
12.	Marital Status	Word	
13.	Status in the Family	Word	
14.	Distributed Fund Packages	Word	

For numeric data continue encoded be normalized, whereas for categorical features do the one-hot-encoding so that every one of these features is expanded into n sub n number of unique features contained category. For the actual class that exists is 0 for Failure and 1 for Sucess in the use of fund. Until this process has been completed and the data preprocessing will proceed to the stage NN. In stage NN, established network scheme feedforward by the number of neurons in the input layer corresponding to the total amount of input feature, n neurons in n hidden layer with each layer contains a bias, and one neuron in the output with a bias that would comparing with actual class that of the dataset as shown in Figure 2:

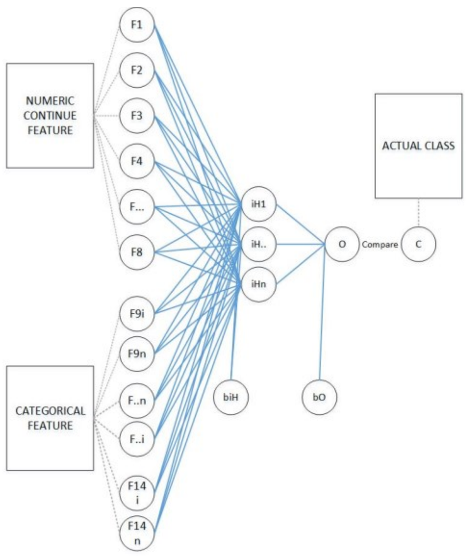

FIGURE 2. THE ARCHITECTURE OF NN- MLP

In the process of learning to use PSO schemes feedforward is applied to each particle in the swarm starts with the initialization parameters of PSO in the form of the number of particle, the dimensions of the search by the total number of neurons and bias in the hidden layer and output layer based initializing NN, the weight of inertia min max, the weight of social c1 and cognitive c2, and the number of iterations.

Learning process starts with the random initialization of position and velocity, as well as the convergence value min max. then carried the weight of inertia generated starting from a minimum value at the beginning of iterations up to a maximum value until the maximum iteration limit. Inertia value obtained in each iteration and then used on the production of the new velocity of each particle in the swarm for determining the position of a new particle in the swarm is a neuron weights and biases at the hidden and output layers. The position used by the feedforward NN in the process of using the data input feature that is activated by Tanh training using weights and biases of existing neurons in the hidden layer that is the position of the particle in PSO. Activation results become input to output layer through the sigmoid activation process with input neuron weights and biases in the position of the particle. The results of the output layer compared with actual class training dataset using the confusion matrix to obtain the value of precision, sensitivity, accuracy, and error as desired. In this study, the value of the desired convergence. Convergence with the best rate obtained from each position of the particle in the swarm pBest later serve and be gBest in the current iteration. gBest obtained is then stored for compared gBest that would be obtained in the next iteration. gBest with the better convergence of gBest previously obtained will be the new gBest. The results of the output layer compared with actual class training dataset using the confusion matrix to obtain the value of precision, sensitivity, accuracy, and error as desired. In this study, the value of the desired convergence. Convergence with the best rate obtained from each position of the particle in the swarm pBest later serve and be gBest in the current iteration. gBest obtained is then stored for compared gBest that would be obtained in the next iteration. gBest with the better convergence of gBest previously obtained will be the new gBest. The results of the output layer compared with actual class training dataset using the confusion matrix to obtain the value of precision, sensitivity, accuracy, and error as desired. In this study, the value of the desired. Convergence with the best rate obtained from each position of the particle in the swarm pBest later serve and be gBest in the current iteration. gBest obtained is then stored for comparing gBest that would be obtained in the next iteration. gBest with the better convergence of gBest previously obtained will be the new gBest. Convergence with the best rate obtained from each position of the particle in the swarm pBest later serve and be gBest in the current iteration. gBest obtained is then stored for comparing gBest that would be obtained in the next iteration. gBest with the better convergence of gBest previously obtained will be the new gBest. Convergence with the best rate obtained from each position of the particle in the swarm pBest later serve and be gBest in the current iteration. gBest obtained is then stored for comparing gBest that would be obtained in the next iteration. gBest with the better convergence of gBest previously obtained will be the new gBest.

Learning process stops when the whole process of iteration n has been done or has found the ideal convergence value in the form of the best models (PSOs are gBest). The process can be seen in Figure 3:

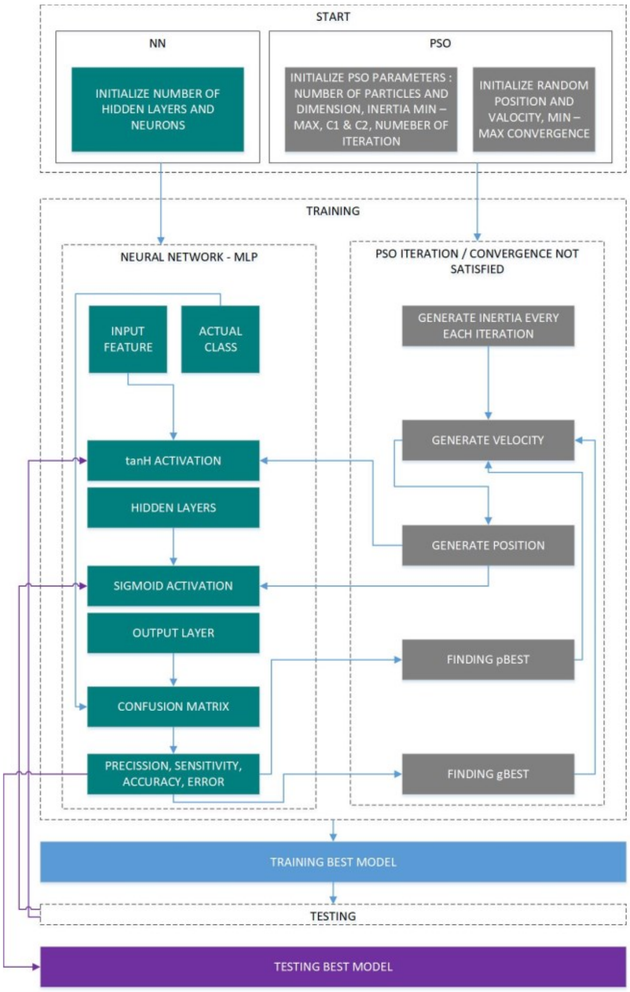

FIGURE 3. MACHINE LEARNING NN - PSO

The best model is found then tested with the data testing to measure the achievements of the model testing by performing feedforward process and without performing further learning process with PSO.

B. *Result And Discussion*

Results of ML using NN-PSO dataset help fisheries with gBest an error value on the confusion matrix is done with three different scenarios ranging from the network structure and parameters that can be seen in Table III with the performance of the achievement of the convergence point differently to the classification results output NN with actual class in the dataset.

A scenario for the structure and value of the small parameter shows the convergence achieved in stages beginning in early iterations, scenario B with the process of convergence achieved with one change before the middle of the iteration process, while the scenario C shows the convergence achieved after the middle of the whole process of iteration. This can be seen in Figure 4-6:

TABLE III. THE SCENARIO OF CONVERGENCE WITH 50 ITERATIONS

N.	***Scen.***	***NN Params (Hidden Layers)***	***PSO Params***	***Convergence***
1.	A	1: 4 neurons 2: 2 neurons	-wmin: 0.4 -wmax: 0.9 -c1: 0:05 -c2: 0:05 -Num. of Particles: 2	-Precision: 0.61 -Sensitivity: 0:44 -Accuracy: 0:58 -Error: 0:42
2.	B	1: 8 neurons 2: 4 neurons	-wmin: 0.4 -wmax: 0.9 -c1: 1.25 -c2: 1.25 -Num. of Particles: 4	-Precision: 0.75 -Sensitivity: 0:48 -Accuracy: 0.66 -Error: 0:34
3.	C	1: 16 neurons 2: 8 neurons	-wmin: 0.4 -wmax: 0.9 -c1: 3.50 -c2: 3.50 -Num. of Particles: 8	-Precision: 0.63 -Sensitivity: 0:48 -Accuracy: 0.60 -Error: 0:40

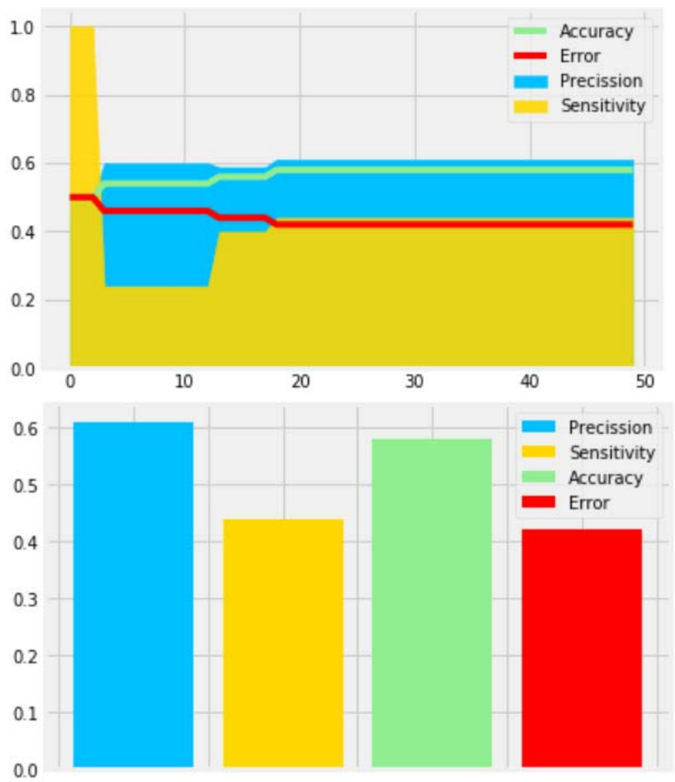

FIGURE 4. CONVERGENCE PERFORMANCE OF SCENARIO A

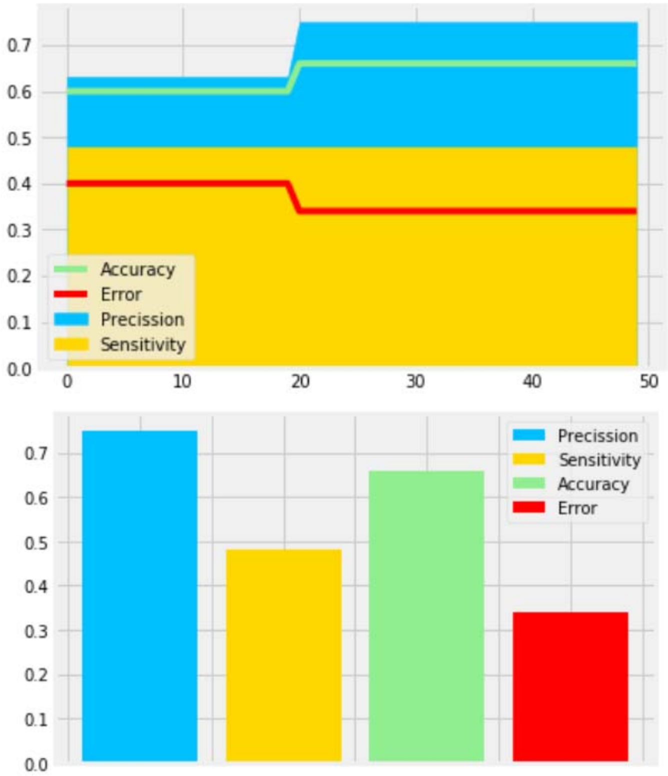

FIGURE 5. CONVERGENCE PERFORMANCE OF SCENARIO B

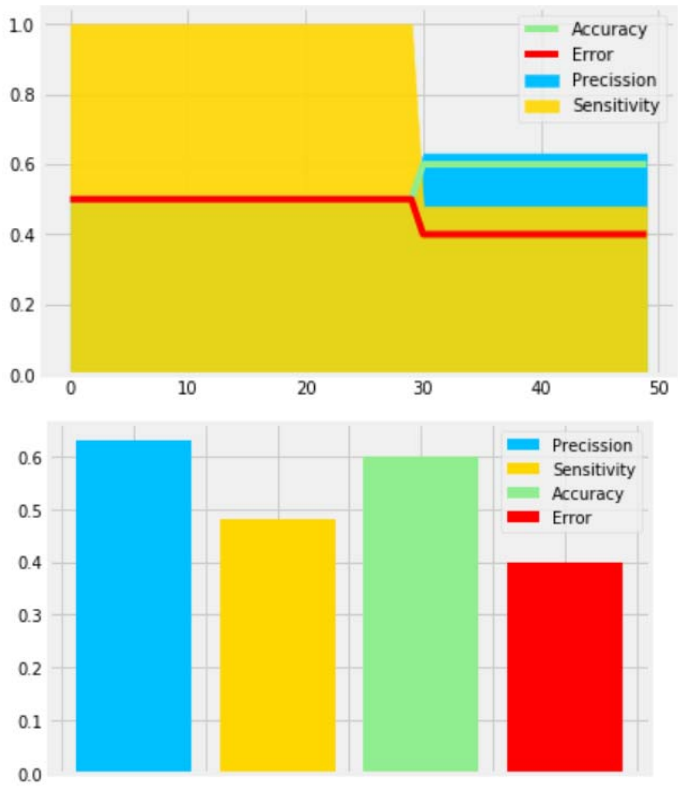

FIGURE 6. CONVERGENCE PERFORMANCE OF SCENARIO C

For best precision obtained with scenario B, the best sensitivity was found in scenario A, the best accuracy found in scenario B, and the best error was found in scenario B. This showed that the ML for the Classification of Fisheries Assistance PSO using NN and achievements of the best model is found in the structure network and parameters of the total number of neurons smaller than the total input features contained in scenario A and B are 4-8 neurons in the hidden layer 1 and 2-4 neurons in the hidden layer 2 by the inertia of at least 0.4 up to 0.9, with the weight of social and cognitive ranged from 0.05 to 1.25 with particle number between 2-4.

V. Conclusion

From the research results, performance models ML with NN and PSO can be applied to the classification process for receiving relief in the quality of fisheries for the achievement of a good model with a high precision with low sensitivity. The sensitivity is higher than error describes an incorrect fraction in the datasets of beneficiaries, and the quantity achieved greater accuracy than half, the error is quite low and does not exceed half of the threshold, and can overcome the overfitting caused by inadequate in the provision of assistance its shown at the confidence of precision as the qualitative measurement is absolutely better than accuracy as quantitative.

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