ISSN:0975-9646



# Estimate Optimum Architecture of SOM Neural Network and Its Weigh Adjustment Using Particle Swarm Optimization

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**Abstract-The artificial neural network plays an important role in data classification. The increasing rate of data diversity need efficient algorithm for the purpose of classification. The complex architecture and weight adjustment process reduces the performance of neural network classifier. In this paper proposed an optimum adjustment of weight and architecture using particle swarm optimization. The particle swarm optimization technique reduces the weight selection process and also optimized the hidden process layer of network. The proposed algorithms implemented in mat lab software and tested well know dataset for the process of classification. In this paper used SOM neural network model for the weight adjustment factor and optimum architecture. The SOM neural network data mapped in two dimensional data space for the mapping of weight of input vector and processing data for the process of clustering technique for the classification of data.**

**Keywords: - Neural Network, SOM, PSO, Optimum**

## I. Introduction

Classification and grouting of data is major issue in data mining process. For the classification and grouping of data used various classification algorithm such as statically classification, binary classification, rule based classification and neural network classification technique. The artificial neural network based classification technique is very important area of research [4]. The artificial neural network based classification technique faced a problem of weight adjustment and activation function. For the adjustment of weight and activation function used various heuristic function and optimization technique. the optimization technique used various algorithm such as genetic algorithm, ant colony optimization and many more optimization algorithm [6]. The architectural/topological design of the ANN has become one of the most important tasks in ANN research and application. It is known that the architecture of an ANN has significant impact on a network's information processing capabilities. Given a learning task, an ANN with only a few connections and linear nodes may not be able to perform the task at all due to its limited capability, while an ANN with a large number of connections and nonlinear nodes may over fit noise in the training data and fail to have good generalization ability [1]. Structural design of an artificial neural network (ANN) is a very important phase in the construction of such a network. The selection of the optimal number of hidden layers and hidden nodes has a significant impact on the performance of a neural network, though typically decided in an adhoc manner [12]. The structure of a neural network is adaptively optimized by determine the number of hidden layers and hidden nodes that give the optimal performance in a given problem domain. Two optimization approaches have been developed based on the Particle Swarm Optimization (PSO) algorithm, which is an evolutionary algorithm which uses a cooperative approach [8]. The optimization of structure of artificial neural network and weight adjustment is challenging issue. The structure and weight adjustment is concern with the performance of data classification. For the optimization of the structure of neural network and weight optimization used particle swarm optimization algorithm. The particle swarm optimization technique is well know dynamic population based optimization technique optimized the weight adjustment of neural network and structure. For the purpose of neural network model used self organized SOM neural network model for the mapping of data and classification of data [9]. The above section discusses the introduction of classification and particle swarm optimization process for the optimization of weight and structure of SOM neural network model. In section II discuss the SOM neural network model. In Section III. Discuss the particle swarm optimization. In section IV discuss the proposed Algorithm and in section V discuss experimental result analysis and finally in section VI discuss the conclusion and future work.

## II. SOM Neural Network Model

In this section discuss the SOM neural network model for the purpose of data classification. The SOM neural network model is unsupervised neural network model. The model consists of two parts winner part and successor part. The winner part of network reduces the radius of classification process. The SOM organizes unknown data into groups of similar patterns, according to a similarity criterion (e.g. Euclidean distance). Such networks can learn to detect regularities and correlations in their input and adapt their future responses to that input accordingly. An important feature of this neural network is its ability to process noisy data [13]. The map preserves topological relationships between inputs in a way that neighboring inputs in the input

space are mapped to neighboring neurons in the map space.
Step 1: Learning rate is set; weights are initialized, Set topological neighborhood parameters.
Step 2: While stopping condition is false, repeat Step 3 – 9
Step 3: For every input vector x, repeat Step 4 - 6
Step 4: For every j, squared Euclidean distance is computed.

$$D(j) = \sum (w_{ij} - x_i)^2 \quad I = 1 \text{ to } n \text{ and } j = 1 \text{ to } m$$

Step 5: When $D(j)$ is minimum find index J,
Step 6: For all units J, with the specified neighbourhood of J, and for all i, update the weights.

$$w_{ij}(\text{new}) = w_{ij}(\text{old}) + \alpha[x_i - w_{ij(\text{old})}]$$

Step 7: Update the learning rate.
Step 8: Decrease the radius of the topological neighbourhood at specified times.
Step 9: Test the stopping condition
Step 10: The learning rate is updated by, $\alpha(t+1) = 0.5\alpha(t)$.

The map formation occurs in two phases:

1. Initial formation of perfect (correct) order
2. Final convergence

The second phase takes a longer duration than the first phase and requires a small value of learning rate. The learning rate is a steadily decreasing function of time and the radius of the neighborhood around a cluster unit also decreases as the clustering process is in progress. The initial weights are considered with random values.

## III. Particle Swarm Optimization

In this section discuss the particle swarm optimization technique. The particle swarm optimization technique optimized the structure and weight of SOM neural network model for the better classification of data. Here discuss the particle swarm optimization algorithm. Particle Swarm Optimization (PSO) is a swarm-based intelligence algorithm [18] influenced by the social behavior of animals such as a flock of birds finds a food source or a school of fish protecting them from a predator. A particle in PSO is analogous to a bird or fish flying through a search (problem) space. The movement of each particle is coordinated by a velocity which has both magnitude and direction. Each particle position at any instance of time is influenced by its best position and the position of the best particle in a problem space. The performance of a particle is measured by a fitness value, which is problem specific. The PSO algorithm is similar to other evolutionary algorithms. In PSO, the population is the number of particles in a problem space. Particles are initialized randomly. Each particle will have a fitness value, which will be evaluated by a fitness function to be optimized in each generation. Each Particle knows its best position pbest and the best position so far among the entire group of particles gbest [7]. The pbest of a particle is the best result (fitness value) so far reached by the particle, whereas gbest is the best particle in terms of fitness in an entire population. In each generation the velocity and the position of particles will be updated as in Eq 1 and 2, respectively. The heuristic optimizes the cost of task-resource mapping based on the solution given by particle swarm optimization technique.

$$v_i^{K+1} = \omega v_i^k + c1rand1 \times (pbseti - x_i^k) + c2rand2 \times (gbest - x_i^k) \ldots\ldots\ldots\ldots\ldots (1)$$

$$x_i^{K+i} = x_i^k + v_i^{k+1} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Where:
$v_i^k$Velocity of particle i at iteration k
$v_i^{K+1}$ Velocity of particle i at iteration k + 1
ω inertia weight
cj acceleration coefficients; j = 1, 2
randi random number between 0 and 1; i = 1, 2
$x_i^k$Current position of particle i at iteration k
pbesti best position of particle i
gbest position of best particle in a population
$x_i^{K+i}$ i position of the particle i at iteration k + 1.

## IV Proposed Algorithm

In this section discuss the modified algorithm of SOM based on particle swarm optimization technique. SOM is a basically a combination of two dimensional matrix structure of neural network. The property of SOM algorithm based on the similar agent of same domain. The process of vector input selection and proceed the data mapping stage is very complex. Now for the minimization of complex input processing used particle swarm optimization algorithm in data mapping phase in SOM processing of algorithm. The particle swarm optimization selects the map data and transfer into grid for the making of cluster. Here describe the steps of SOM along with particle swarm optimization.

Step1. Initially the data passes through the PSO and PSO define and initialized data in terms of particle and decide random size of population N=1000.

a. Define the velocity of particle in terms of data point difference value
b. Define the value of fitness constraints for the selection of data for the process of neuron

$$L_k\left(M_{i,R_j}\right) = \frac{[\tau(M_i,R_j)]\alpha[\rho(M_i,R_i)]\beta}{\sum_{h\epsilon lk(Mi,Rj)}[\tau(Mi,h)]\alpha[\rho(Ri,h)]\beta}, Ri\epsilon Lk(Mi,Ri) \ldots\ldots\ldots\ldots.. (4.5.1)$$

Here $\tau(Mi, Ri)$ is the value of attribute and mapping for neuron

c. Iteration process is done and calculate the value of Gbest and Pbest
d. Passes data through SOM

Step2. Here show steps of processing of SOM

1) Process the PSO data and initialized the number of neuron.
2) Randomly select the PSO vector for the process of weight optimization.
3) Every ant is examined to find the best match PSO.
4) The similarity of PSO vector is decrease and the number of optimal PSO is going to successor phase.

5) After that the weight value of vector are adjusted and passes through the PSO space of cluster map.
The function PSO mapping creates data matrix of neuron.
Input the PSO space of cluster generated PSO Matrix.

1. estimate the PSO and NEURON correlation attribute as

$$\mathrm{Rel}(a,b) = \frac{\mathrm{cov}(a,b)}{\sqrt{\mathrm{var}(a)\times\mathrm{var}(b)}}$$

Here a and b the PSO vector of PSO matrix

2. The estimated correlation coefficient of PSO passes through cluster.

$$x(t) = w0 + \sum_{j=1}^{\text{total data}} wj \exp\left(\frac{-(\text{total} - xj)}{\sigma^2}\right)$$

3. create the relative PSO difference value

$$Rc = \sum_{k=1}^{r}\sum_{i=1}^{m}(hi - h)(eik - et)$$

4. After processing of this of PSO data creates cluster.
5. Generate PSO mapping of each cluster according to the unseen data.
6. The cluster measures the Similarity and return the equivalent cluster of data.
7. If the relevant cluster are not found that the process going again in PSO space.

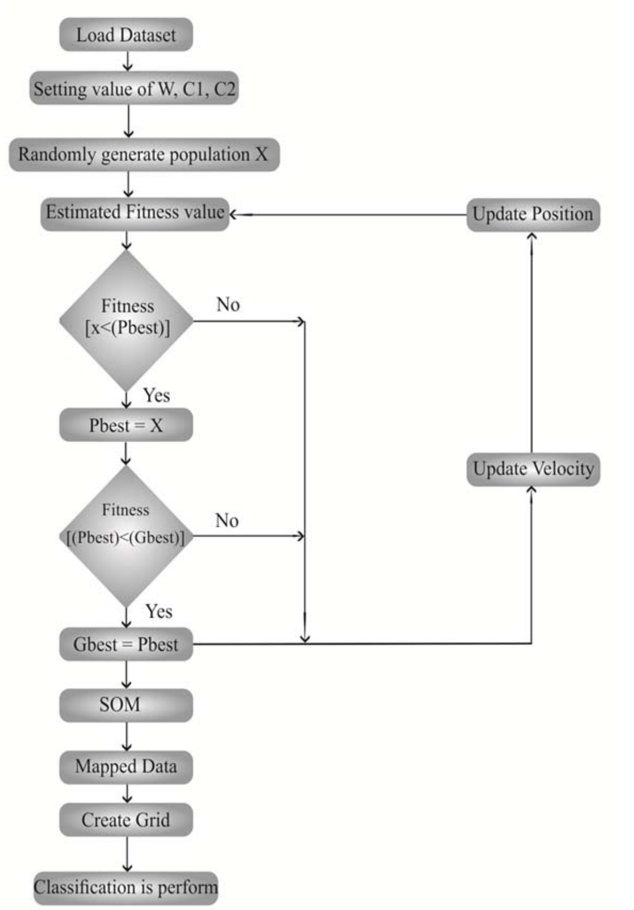


**Figure 1 show that block diagram of classification process PSO with SOM neural network Model.**

## V Experimental Analysis

To evaluate the performance of proposed method of artificial neural network based classifier for the classification of data used MATLAB software 7.8.0 with a variety of dataset used for experimental task. In this dissertation perform experimental process of proposed structure optimization technique. The proposed method implements in MATLAB 7.14.0.739 and tested with very reputed data set from machine learning research center.

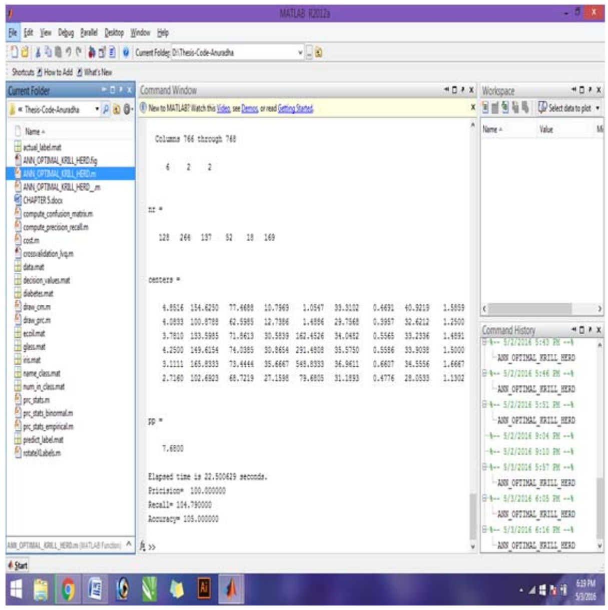

Figure 2: Shows the result window with Diabetes, Pricision and Recall for using Kill Herd Algorithm with input lemda value 3.

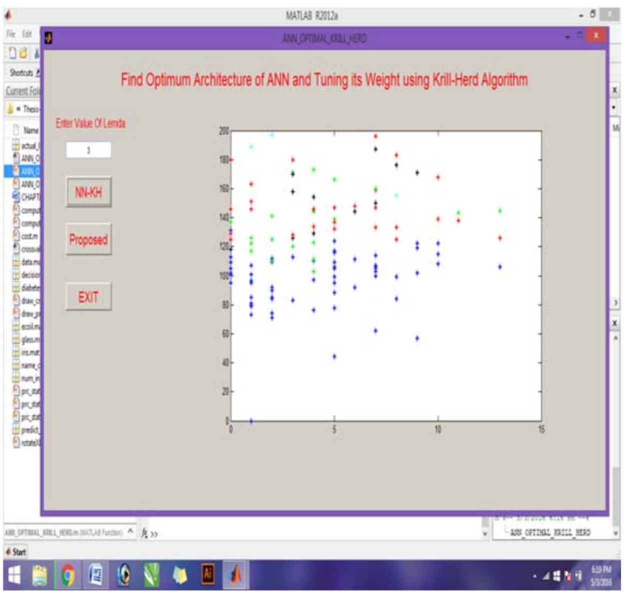


Figure 3: Shows the result window of Image with Diabetes and selected input lemda value 3 for using Kill Herd Algorithm.

**Table 1:** Comparative performance evaluation for the performance parameter of Diabetes using Kill Herd Algorithm and Proposed.

| **Input values** | **Kill Herd Algorithm** | | | **Proposed** | | |
|---|---|---|---|---|---|---|
| **Lemda** | Pricision | Recall | Accuracy | Pricision | Recall | Accuracy |
| 3 | 90.0 | 94.7 | 95.0 | 92.0 | 89.8 | 96.0 |
| 5 | 79.0 | 98.2 | 84.0 | 81.0 | 98.2 | 85.0 |
| 7 | 73.0 | 96.4 | 78.0 | 75.0 | 99.9 | 79.0 |

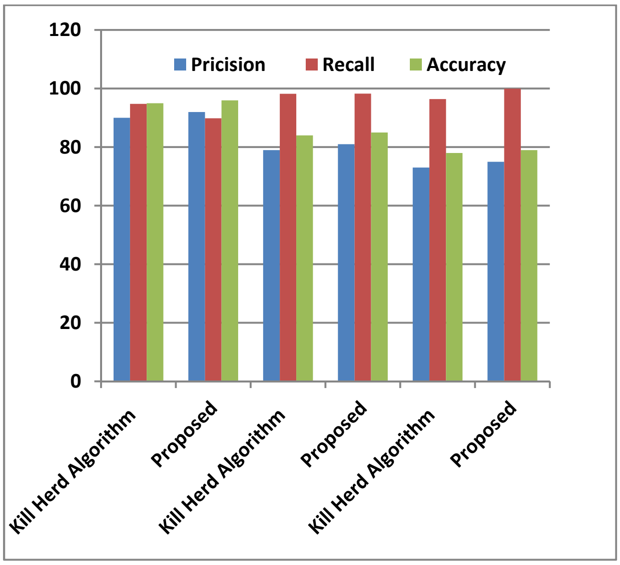


Figure 4: Shows the comparative performance graph for Kill Herd Algorithm and Proposed algorithm with the **input value of Lemda 3, 5 and 7** in Diabetes. Results shows that the Proposed algorithm is always better than the existing method.

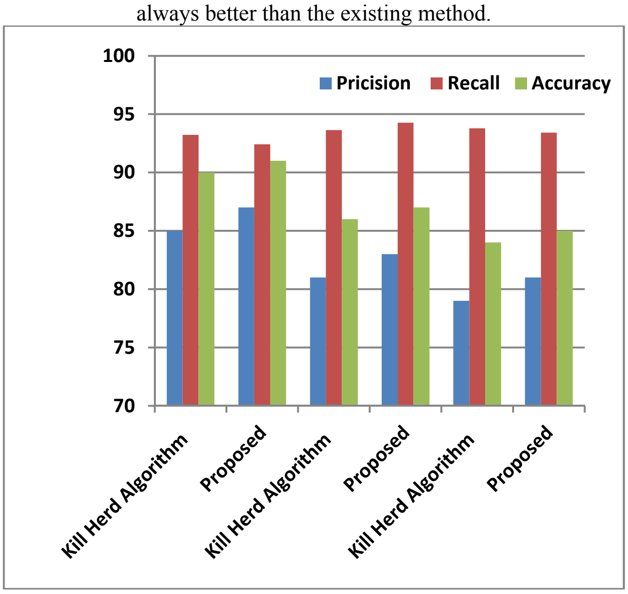


Figure 5.: Shows the comparative performance graph for Kill Herd Algorithm and Proposed algorithm with the **input value of Lemda 3, 5 and 7** in Ecoil. Reults shows that the Proposed algorithm is always better than the existing method.

## VI CONCLUSION & FUTURE WORK

In this paper modify the SOM classification technique using particle of swarm optimization. The particle of swarm optimization used for the structure and weight value. The optimal selection of structure and weight value increases the accuracy of class technique. The class technique imposed the two processes for the selection of structure and weight parameter. Modified SOM algorithm for classification of large data, can compute weights for views and individual variables simultaneously in the classification process. With the two types of weights, compact views and important variables can be identified and effect of low-quality views and noise variables can be reduced. Therefore, proposed method can obtain better classification results than individual variable weighting classification algorithms from large data. The POS algorithm takes more time for the selection of estimated value of weight. The values of weight influence the class quality during process of data. In future optimization technique can be used for self-selection of optimal class for large data.

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