Indian Journal of Science and Technology, *Vol 10(15), DOI: 10.17485/ijst/2017/v10i15/108270, April 2017*
ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645

Structural Redesign of Artificial Neural Network for Predicting Breast Cancer with the Aid of Artificial Bee Colony

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Abstract

Objectives: In apparent, the core intention is to predict breast cancer stage such as benignant or malignant with different techniques from Breast Cancer Wisconsin (original) benchmark dataset. **Methods/Statistical Analysis:** When compared through every other tumor, breast cancer is solitary of the actual causes for death in women. To forecast the result of several diseases or find genetic activities of tumors, the breast cancer data could be valuable from the classification. In this work, the proposed method is Artificial Neural Network (ANN) classification with Artificial Bee Colony Optimization (ABC) technique. **Findings:** Artificial Neural Network (ANN) structure is worked and in this structure training algorithms is utilized and the proposed is Levenberg-Marquardt technique. Artificial Bee Colony Optimization (ABC) technique is used to optimize the hidden layer and neuron of ANN. In the outcome, best validation performance is predicted and the different execution assessment measurements for two optimization algorithms are investigated. **Application/Improvements:** The comparison performance graph for Accuracy, Sensitivity and Specificity are foreseeing for the most part the precision worth is 95.9% in favor of Artificial Bee Colony Optimization technique.

Keywords: ANN and ABC, Levenberg-Marquardt

1. Introduction

The majority of general cancers between women were standout as breast cancer. It is an individual of significant reasons for death in women when contrasted with every single other disease. Cancer is a kind of illnesses, which causes the cells of the body to modify its attributes and cause anomalous development of cells[1]. Breast cancer screening should be possible utilizing diverse imaging methods. The most well known screening strategy is the mammography. This sort of imaging strategy is a particular type of radiography that utilizations radiations lower than those of ordinary radiography, for example, routine x-ray[2]. Breast cancer patients are portrayed by large amounts of endogenous estrogens. Nevertheless, just around 18% of these patients are beneath 50 years old, and most breast cancers are analyzed in women who are postmenopausal[3]. The World Health Organization assesses the quantity of breast cancer determination to be women consistently among 1.2 million as indicated by projections[4]. Various analytic tests and strategies are accessible for recognizing the occurrence of the disease. One of these is examination of a biopsy taken since the breast[5]. Less normally, breast cancer can start in the stromal tissues which incorporate sinewy connective tissues and greasy of the breast. It is generally trusted that the breast cancer is brought on by a hereditary abnormality[6]. Breast ultrasound (BUS) is the main essential assistant to mammography for patients through discernable masses and typical or uncertain mammograms. Radiologists execute BUS image examination by watching morphological and texture distinctiveness of breast lesions[7]. Despite the fact that breast cancer disease is still a noteworthy reason for death from cancer in women, the breast cancer

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mortality shows a diminishing rate with the assistance of early recognition of tumor, fitting treatment and exact treatment[8].

Early detection of breast cancer can be accomplished utilizing Digital Mammography, normally through identification of Characteristics masses and/or small-scale calcifications. A mammogram is an x-ray of the breast tissue, which is intended to recognize abnormalities[9]. Mammography is the highest quality level for finding the breast cancer; however, as a screening device yet the sensitivity and specificity of it is bit low[10]. This kind of issue is happened because of human blunder. Un-right readings of mammogram are called false positive and false negative readings of mammogram[11]. Masses are one of the critical indications of early bosom malignancy. They are regularly indistinct from the encompassing parenchyma in light of the fact that their components can be clouded or be like that of ordinary inhomogeneous bosom tissues[12]. Thus, bosom growth indicative and prognostic issues are primarily in the extent of the broadly examined characterization problems[13]. The order of Breast Cancer information can be helpful to foresee the result of a few sicknesses or find the hereditary conduct of tumors. There are numerous strategies to foresee and arrangement bosom growth pattern[14].

The significant sorts of contingent estimations comprise: 1. Decision trees 2. Naive Bayesian 3. Genetic algorithms 4. Artificial Neural Networks 5. k-nearest neighbor algorithms prognosis 6. Linear discriminate analysis[15]. Nonlinear data preparing gadgets are Artificial Neural Networks (ANN), worked from interconnected basic handling gadgets called neurons enlivened by the way natural anxious systems[16]. Computational frameworks are artificial neural networks whose idea is gotten since organic neural networks. An ANN comprises of a gathering of handling components that are exceedingly interrelated and change an arrangement of contributions to an arrangement of coveted outputs[17]. This paper portrays neural system ways to deal with breast cancer finding. Neural systems have been generally utilized for breast cancer analysis. In any case, the greater part of these applications accepted predefined system design (counting network and hub exchange works) and utilized a training algorithm[18].

[19]Had proposed breast cancer was a standout amongst the driving reasons for death among women. The early recognition of variations from the norm in breast enables the radiologist in diagnosing the breast cancer effortlessly. Proficient devices in diagnosing the dangerous breast will help the restorative specialists in accurate diagnosis and auspicious treatment to the patients. In this work, an investigation was done utilizing Wisconsin Diagnosis Breast Cancer database to characterize the breast cancer as either kindhearted or harmful. Supervised learning algorithm -Support Vector Machine (SVM) with portions like Linear, and Neural Network (NN) are utilized for correlation with accomplish these undertakings. The exhibitions of the models are broke down where Neural Network approach gives more 'accuracy' and 'precision'.

[20]Had suggested that in any case, by analysts the exact categorization of breast cancer was motionless a therapeutic assessment faced. To propose a framework for analysis, anticipation and expectation of breast anomaly utilizing Artificial Neural Network (ANN) models in light of two-dimensional wavelet transform. The primary methodology involves the preprocessing venture for breast profile extraction, completed by killing the low frequency components of the mammogram; deserting sub groups containing high frequency coefficients, in light of miniaturized scale calcifications imply high frequency coefficients. The following methodology includes features extraction got from wavelet decomposition analysis. The last approach was alluded to as the classification stage that uses back propagation neural network to recognize unusual tissue from ordinary ones. The proposed system was tried on the MIAS database, resulting about 91.64% progression rate of classification.

[21]Had advised that the most style of dangerous tumor saw in women is breast cancer and the successful handling depends on upon its premature diagnosis. For breast cancer, diagnosis since histopathological images leftovers the "gold standard". For classification of cell nuclei, 138 textural features and 4 shape-based features in view of shading spaces are removed. Through, support vector machine (SVM) among chain-like agent genetic algorithm (CAGA) optimal feature set was obtained. The proposed strategy was tried on 68 BCH images enclosing more than 3600 cells. Investigational consequences demonstrate that the mean segmentation specificity was 91.64% (74.07%) and sensitivity was 91.53% (74.05%). The classification presentation of typical and dangerous cell images can do 96.19% (70.31%) for accuracy, 93.33% (70.81%) for specificity and 99.05% (70.27%) for sensitivity.

[22]Had proposed Breast cancer prevails as one of the scandalous haunting illnesses amid women global wide.

Premature detection and handling of breast cancer can make the survival charge of patients. For synchronous feature selection and parameter optimization of ANN, this paper presents a programmed breast cancer analysis procedure utilizing a genetic algorithm (GA). The proposed algorithms known as GAANN_RP creates the best and normal, 99.43% and 98.29% right order individually on the Wisconsin Breast Cancer Dataset.

[23]Had proposed a structure using clustering systems, which recognizes the malignancy stage. The task was accomplished one of a form example of unsupervised learning using Adaptive Resonance Neural Network (ARNN). Subsequently helps in scheming the precision of the trained network and a vigilance parameter (vp) in ARNN describes the ending measure. The estimation of ARNN was incontestable by utilizing Wisconsin breast cancer database. The information open within the UCI information storage facility contains 699 cases out of that tend to used 600 cases to train the system. During this dataset, there are 225 as harmful cases and 375 obliging cases. See that at vp=0.2 the system has Precision is 79% and Recall is 75% and ordinary Accuracy=82.64%.

2. Proposed Methodology

In the proposed work, fundamental target is to produce a big data from benchmark dataset with its recommended limitation for those utilizing input parameters, to be specific Sample code number, Uniformity of Cell Size, Bland Chromatin, Single Epithelial Cell Size, Normal Nucleoli, Clump Thickness, Mitoses, Marginal Adhesion, Bare Nuclei and Uniformity of Cell Shape. The yield is two unique classes, for example, benignant and malignant. For arranging these classes Artificial Neural Network (ANN) classification is used and in this default ANN structure nine training algorithms for moment Levenberg-Marquardt, BFGS Quasi-Newton, Resilient Back propagation, Scaled Conjugate Gradient, Fletcher-Powell Conjugate Gradient, Variable Learning Rate Back propagation, Conjugate Gradient with Powell/Beale Restarts, One Step Secant and Polak-Ribiere Conjugate Gradient is utilized to find the superior training algorithm. In the wake of training the Levenberg-Marquardt is the proposed algorithm and the artificial neural network consist of three layers, for example, input layer, hidden layer and output layer. The artificial neural network encompasses of ten neurons for all five hidden layer. For enhancing the ANN structural design (neuron and hidden layer) different optimization techniques is included, in favor of occasion artificial bee colony and particle swarm optimization then predicts the big data from benchmark dataset.

2.1 Artificial Neural Networks (ANN)

Artificial intelligence and in perceptive psychology, the considerable learning approach ANN is utilized. It is a modified computational model, which means to copy the network structure and working of the human mind. ANN is comprised of an interrelated structure of artificially produced neurons which capacity as trails for information transmits. These network structures are adjustable and adaptable, learning and altering between each different interior or exterior incentive. ANN's are used in series and pattern recognition systems, modeling, data processing, and robotics.

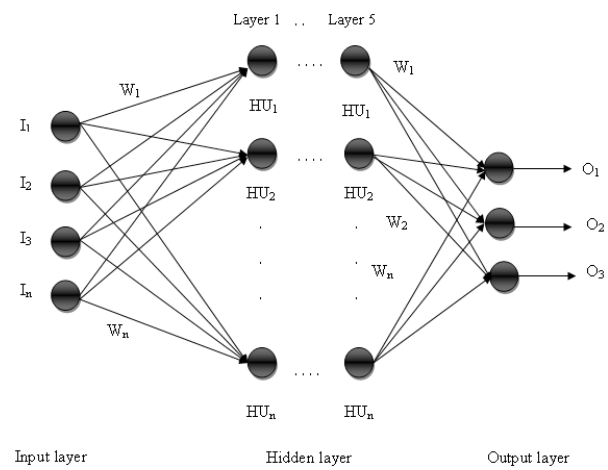


Figure 1. Neural network structure.

Overall, figure 1 neural network structure absorbs input, hidden and output layer. Number of neurons involved, by each layer of the artificial neural network. Each neuron in the input layer is associated by the hidden neuron in this, and every hidden neuron is joined with output layer through an unpredictable weight. The unpredictable weights, allotted to every interrelated layer.

2.1.1 Initialization

In this procedure, ten inputs based the hidden weights w_{ij} and input layer weight w_j are established.

2.1.2 Input Layer

Various parameters are used in the input layer such as Sample code number, Uniformity of Cell Size, Bland

Chromatin, Single Epithelial Cell Size, Normal Nucleoli, Clump Thickness, Mitoses, Marginal Adhesion, Bare Nuclei and Uniformity of Cell Shape. The inputs $K_1, K_2, ...K_n$ are associated to the input neurons $u_1, u_2, ...u_n$. Every neurons in the input layer is linked among the hidden neurons among a random weight $w_{11}, w_{12}, ...w_{ij}$

The fundamental function of hidden neurons is estimated based on the equation underneath,

$$Y_f = \sum_{j=1}^{N} K_i \times w_{ij} \tag{1}$$

Wherever w_{ij} is an input layer weight, Y_f is a fundamentals function, and i is a number of inputs through this basic function the active function is joined.

In this sigmoidal function, the activation purpose of hidden layer neurons is estimated and implemented based on the equation revealed beneath,

$$\tan sig\,(Y_f) = \frac{n}{(1+\exp\ (-n * Y_f)) - (n-1)} \tag{2}$$

In the appearance of a hyperbolic tangent, multilayer perceptrons is a sigmoidal activation function. Hidden layer is the upcoming layer of ANN.

2.1.3 Hidden Layer

Hidden layers as five numbers are exposed and in every hidden layer, 10 neurons are executed in this section. Two hidden layers is improved in attainment by utilizing Levenberg-Marquardt algorithm and by this neuron activation function and basic function are calculated and insert an weight to estimate the output layer. In the hidden layer number of neurons is defined as $Hu_1, Hu_2, ...Hu_n$, that are linked with the output layer neuron. Every neurons in the hidden is associated through the output neurons amid a random weight $w_1\ , w_{12}, ...w_{ij}$

2.1.3.1 Levenberg-Marquardt Algorithm

The majority of utilized optimization training algorithm is Levenberg-Marquardt algorithm. In a wide assortment of issues, Levenberg-Marquardt algorithm beats simple gradient descent and further conjugates inclination techniques. This algorithm is a second order technique that multiple occasions is ignored by individuals endeavoring to train neural networks, perhaps in light of the fact that it is extra perplexing to actualize than EBP. Nevertheless, it certainly compensates for this in prevalent execution. Levenberg-Marquardt is like EBP in that it involved the computation of the gradient vector, yet likewise, Levenberg-Marquardt additionally figures the Jacobian. Below equation, expose the gradient vector:

$$p = \begin{matrix} \frac{\partial B}{\partial w_1} \\ \frac{\partial B}{\partial w_2} \\ . \\ . \\ . \\ \frac{\partial B}{\partial w_n} \end{matrix} \tag{3}$$

Where W refers to the weights and B is there error of the network for that prototype. The Jacobian is fundamentally each slope for all training prototype and network output. Underneath exposed the Jacobian formula.

$$JC = \begin{matrix} \frac{\partial B_1}{\partial w_1} & \frac{\partial B_1}{\partial w_2} & ..... \frac{\partial B_1}{\partial w_n} \\ ..... & ..... & ...... \\ \frac{\partial B_2}{\partial w_2} & \frac{\partial B_2}{\partial w_2} & ..... \frac{\partial B_2}{\partial w_n} \\ ..... & ..... & ...... \\ \frac{\partial B_n}{\partial w_1} & \frac{\partial B_n}{\partial w_2} & ...... \frac{\partial B_n}{\partial w_n} \end{matrix} \tag{4}$$

Everywhere K is the number of patterns, also N is the number of weights. Formerly the Jacobian is deliberated, the Levenberg-Marquardt algorithm will be symbolized by the subsequent:

$$W_{RL} = W_R - \ (JC_R^{\ T} JC_R + \mu KE\ )^{-1} JC_R^{\ T} B \tag{5}$$

Where, KE is the character system, l is a learning parameter and B is the total error for all illustrations. While, l is comparable to zero it is the Newton Method and exactly when l esteem is huge the LM algorithm gets the opportunity to be steepest decent or BP. The entire system is then reiterated pending the misstep is diminished to the essential worth. This second demand algorithm is basically speedier than BP. For little systems with only some training prototypes, this is not a critical problem, yet rather for frameworks among numerous training prototypes, it is additionally raised. To take longer than emphasis for BP, this inversion will achieve each training iteration for Levenberg-Marquardt. The time required for planning will at present be far not as much as that of BP, in light of the fact that the LM will require such only some iterations.

In ANN structural design for optimizing the different techniques are used such as ABC and PSO within this ABC algorithm is the proposed one, it accomplished superior in the structure.

2.1.3.2 Artificial Bee Colony Optimization Algorithm

2.1.3.2.1 Initial Solution Generation

The Initial solution (I_i) is generated randomly and is utilized as initial solution.

2.1.3.2.2 Fitness Computation

The Fitness computation is the process, which utilizes Equation (3) to find the fitness of the individual solution, and this process is evolving as follows.

$$F_i = \min(\sum_{k=1}^{x} I_i) \qquad (6)$$

The Minimum of fitness is considered to be the best fit.

2.1.3.2.3 Employed Bee

Beneath the specified equation, employed bee is the procedure somewhere the new solution is produced.

$$ES_{ij} = I_i + \Phi_{ij}(I_i + I_k) \qquad (7)$$

Equation (7) is used to produce the new solution in the defined solution *i*, *ij* designates the index position and wherever as in Φ_{ij} , Φ range starting [-1, 1] and *k* established randomly $k \in \{1, 2 \ldots \text{size } (i)\}$ the consequence restriction in this procedure $k \neq i$. Through Equation (7), the Fitness computation procedure is held up for estimating the fitness for the newly created solution. Then the greedy selection GS_{ij} procedure is achieved to retrieve the best solution since the currently created ES_{ij} and I_i .

2.1.3.2.4 Probability Calculation

The Probability calculation (p_i) is calculated for the GS_{ij} as per the procedure exposed beneath.

$$p_i = \frac{F_i}{\sum_{i=1}^{x} F_i} \qquad (8)$$

Behind the greedy selection procedure, the beyond Equation (8) is the procedure to find out the probability rate of accomplished fitness. Following achievement of the probability calculation procedure the accomplished solution is in the sort that the fitness has superior probability priority rate.

2.1.3.2.5 Onlooker Bee

The solution is arranged and treated as the initial solution for the onlooker bee section, consequent to the probability rate computation. Based on the abovementioned solution, the fitness is calculated for OS_{ij} and new solution (OS_{ij}) is estimated by utilizing Equation (7). Once more, the greedy selection procedure is executed in order to select the best solution among the currently stirring onlooker bee solution $OS_{ij}(F_i)$ and the probability based greedy solution stirring in the earlier step.

2.1.3.2.6 Scout Bee

The Scout honey bee happens when the forsook solutions happen and it is rehashed constantly until the scout limit, which will prompt the reason for random solution as has happened beforehand. In this work, as far as scout limit is set as two, when the deserted solution surpasses two then the previously mentioned irregular arrangement fulfilling the requirements will happen.

2.1.4 Output Layer

The output layer are related through hidden neurons and every association has a weighted esteem, for example, $w_1, w_2, \ldots\ldots w_n$. The activation function and basis function is happened through the weight and output is anticipated.

3. Result and Discussion

In this segment, big data is generated from benchmark dataset with its constraint. The input parameters namely Single Epithelial Cell Size, Uniformity of Cell Size, Sample code number, Normal Nucleoli, Bare Nuclei, Uniformity of Cell Shape, Mitoses, Marginal Adhesion, Clump Thickness and Bland Chromatin is used. The output is three different classes such as beginning, middle and final class. For predicting outputs different training algorithms utilized in neural network structure and for optimizing hidden layer and neuron the optimization techniques such as ABC and PSO is occurred. The evaluation metrics is find for these two algorithms namely Accuracy, Specificity, Sensitivity, False Negative (FN), False Positive (FP), True Negative (TN), True Positive (TP), False Positive Rate (FPR), Positive Predictive Value (PPV), False Negative Rate (FNR), Negative Predicted Value (NPV) and False Discovery Rate (FDR).

3.1 Best Validation Performance Graph

Figure 2 has been appeared beneath best validation performance diagram. In this diagram mean squared mistake fluctuate 10^{-2} to 10^{1} and the ages differ 0 to 11 the preparation begins from above 10^{0} mean squared blunder and marginally diminish up to 10^{-1} in 1 epochs on the other hand lessening to 2 epochs in mean square error 10^{-14} and constant to 3 epochs. Once more somewhat, abatement up to 10^{-2} in 11 epochs.

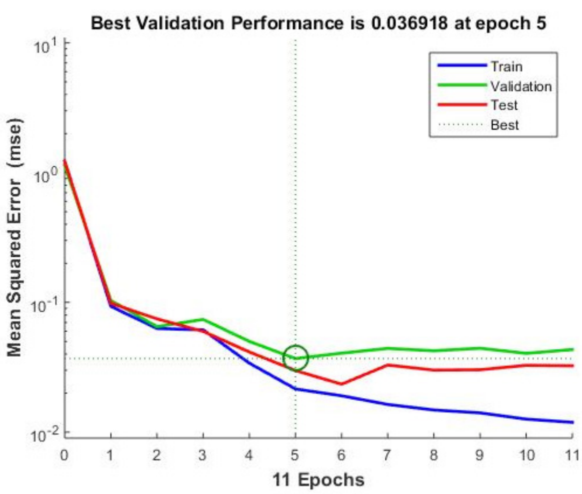


Figure 2. Best validation performance at 11 epochs.

For validation, the mean square error starts from above 10^{0} then reduced up to 10^{-1} in epochs 1 and over diminished to 11 epochs in 10^{-17} mse. For testing the mean squared error varies from above 10^{1} and decrease to 11 epochs up to 10^{-18} mse. In this, the best validation presentation is 0.036918 at epoch 5.

3.2 Default Network Structure

In the default artificial neural network, two distinctive training optimization techniques are utilized to optimize the hidden layer and neuron. To predict the optimal neural network structure technique to be explicit ABC and PSO are utilized. In light of these algorithms ABC is used and optimized the hidden layer and neuron it foresee the better artificial network structure design.

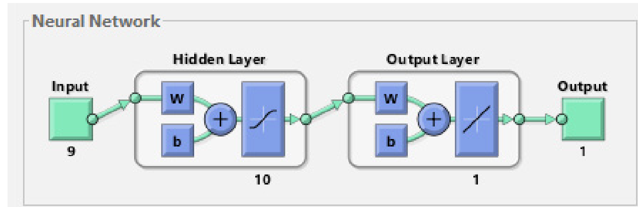
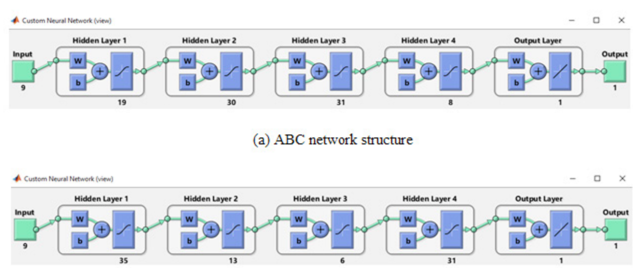


Figure 3. Default network structure.

In figure 3 the default network structure has shown. In this 9 input layer, 1 hidden layer among 10 neurons and 1 output layer are considered.

3.3 Network Structure for Two Optimization Algorithms

Figure 4 system structures in light of two algorithms hidden layer and neuron is altered. For ABC algorithm 9 input layers, 4 hidden layers and 1 output layer are measured. In hidden layer 1, the neuron is 19, hidden layer 2 the neuron is 30, hidden layer 3 the neuron is 31 and hidden layer 4 the neuron is 8.



(a) ABC network structure

(b) PSO network structure

Figure 4. Neural network structure for PSO and ABC algorithms.

For Particle Swarm Optimization (PSO) the input and output layer is general and hidden layer 1 the neuron is 35, hidden layer 2 the neuron is 13, hidden layer 3 the neuron is 6 and hidden layer 4 the neuron is 31. Finally, ABC is better while comparing with other optimization techniques.

Table 1 shows, the various parameters such as False Positive (FP), False Negative (FN), True Positive (TP), True Negative (TN), Negative Predicted Value (NPV),

Table 1. Various performance evaluation metrics for two optimization algorithms

Techniques	TP	TN	FP	FN	PPV	NPV	FPR	FNR	FDR
Default	90	39	10	2	0.9	0.95122	0.20408	0.02174	0.1
ABC	91	45	4	1	0.95789	0.97826	0.08163	0.01087	0.04211
PSO	91	34	15	1	0.85849	0.97143	0.30612	0.01087	0.14151

False Negative Rate (FNR), Positive Predictive Value (PPV), False Positive Rate (FPR) and False Discovery Rate (FDR) are evaluated for two algorithms such as ABC and PSO in this ABC algorithm is improved comparing with default and PSO algorithm.

3.4 Comparison Performance of Two Optimization Techniques

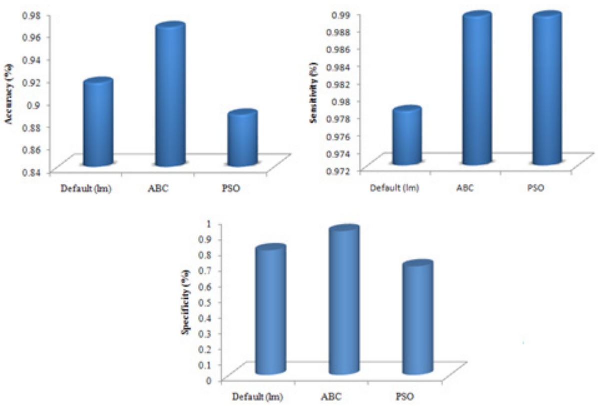


Figure 5. Comparison performance of two optimization techniques.

In figure 5, the comparative performance of two optimization methods is indicated. In this, accuracy, specificity and sensitivity performance of various systems, in particular PSO and ABC are connected where the Accuracy estimation of ABC is higher than the default and PSO algorithms.

4. Conclusion

In this portion for classifying the module of breast cancer illness, the different input parameters utilized. The Artificial Neural Network structure is utilized and in this structure nine training algorithms particularly Levenberg-Marquardt, Scaled Conjugate Gradient, Fletcher-Powell Conjugate Gradient, Variable Learning Rate Back propagation, Conjugate Gradient with Powell/Beale Restarts, BFGS Quasi-Newton, Polak-Ribiere Conjugate Gradient, Resilient Back propagation and One Step Secant is utilized to locate the better training algorithm. The Levenberg-Marquardt algorithms are proposed and in this for planning the structure, optimizing hidden layer and neuron the other two-optimization algorithm is performed. From the outcome best approval execution is 0.036918 at age 5 has been utilized and an assortment of assessment measurements are analyzed, for example, False Positive (FP), False Negative (FN), True Positive (TP), True Negative (TN), Negative Predicted Value (NPV), False Positive Rate (FPR), False Negative Rate (FNR), Positive Predictive Value (PPV), False Discovery Rate (FDR), Accuracy, Sensitivity and Specificity. In this, Accuracy quality is 95.9% for Artificial Bee Colony (ABC) technique. In future, other different strategies are utilized to produce the big data from the benchmark.

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