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Networks Data Transfer Classification Based On Neural Networks

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ABSTRACT: Data transmission classification is an important issue in networks communications, since the data classification process has the ultimate impact in organizing and arranging it according to size and area to prepare it for transmission to minimize the transmission bandwidth and enhancing the bit rate. There are several methods and mechanisms for classifying the transmitted data according to the type of data and to the classification efficiency. One of the most recent classification methods is the classification of artificial neural networks (ANN). It is considered one of the most dynamic and up-to-date research in areas of application. ANN is a branch of artificial intelligence (AI). The neural network is trained by backpropagation algorithm. Various combinations of functions and their effect while utilizing ANN as a file, classifier was studied and the validity of these functions for different types of datasets was analyzed. Back propagation neural university (BPNN) supported with Levenberg Marqurdte (LM) activation function might be utilized with as a successful data classification tool with a suitable set of training and learning functions which operates, when the probability is maximum. Whenever the maximum likelihood method was compared with backpropagation neural network method, the BPNN supported with Levenberg Marqurdte (LM) activation function was further accurate than maximum likelihood method. A high predictive ability against stable and well-functioning BPNN is possible. Multilayer feed-forward neural network algorithm is also used for classification. However BPNN supported with Levenberg Marqurdte (LM) activation function proves to be more effective than other classification algorithms.

Keywords: Data Transmission, Levenberg Marqurdte (LM) Activation Function, Back Propagation Neural University (BPNN), Artificial Neural Networks (ANN)

1. INTRODUCTION

The amount of data is advancing at an exponential rate, and in order to extract useful information from it, it is necessary to analyze such enormous amount of data. The field of data mining emerged as a result of this. The extraction of knowledge along such a large sum of databases is referred to as data mining. Information mining is center of KDD operation. KDD is coordinated course of recognized, legitimate, novel, helpful and reasonable example from enormous and complex dataset. [1].Tasks involving data mining fall towards two categories: expressive and prescient. Time series analysis, classification, and regression are examples of predictive tasks, whereas clustering and association rules are examples of descriptive tasks [2].Such approaches might be utilized in particular areas. Talk about these techniques and how they might be applied in various fields. Applications for data mining can be found in a wide range of fields, containing banking, insurance, medicine, finance, marketing, healthcare, and sales [3, 4] .An method of data mining called classification is used to predict the class of objects. It's a good demonstrating of supervised learning. The categorical label is predicted by classification (discrete, ordered).There are two steps involved in data classification. A classifier is built to describe a

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predetermined set of data classes during the learning (or training) step of the early step. The first-stage model is used in the second step to classify unknown data, and test data are used to estimate the classifier's accuracy. Decision tree, K nearest neighbor, naive Bayesian classifier, and artificial neural network are just a few of the classification algorithms available [5, 6] provides an examination of these classification algorithms in comparison. An artificial neural network is a method of machine learning used to solve classification issues.

It is usually referred to as the neural network model and is a branch of artificial intelligence or Artificial Neural Networks (ANNs). The ANN learns the system to perform the mission, rather than programming an algorithm to perform specific tasks. to achieve such synthetic tasks. The AI system is being created as an operating model which might find patterns buried in data that replicate useful knowledge quickly and accurately. Neural networks are one case of AI schemes, being that AI systems should discover from data on a consistent basis in regions Medical diagnosis using dissimilar data, the utmost available techniques are Artificial intelligence technologies. An artificial neural network consists of various artificial neurons linked together according to the design network geometry. The objective of a neural network is to convert inputs to important outputs. Learning placement might be supervised or unsupervised. Neural Networks actually learn in the presence of noise. Data Classification is a two stages process: (1) the preparation (or learning) stage and (2) the test (or assessment) stage where the genuine class of the occasion is contrasted and the anticipated class. On the off chance that the hit rate is OK to the examiner, the classifier is acknowledged as being fit for grouping future cases with obscure class. Characterization of data is a two-step process: (1) the preparation (or learning) stage and (2) the testing (or assessment) stage where the real class of the case is contrasted with the normal class. In the event that the hit rate is OK to the parser, the classifier is acknowledged as having the option to group future occurrences with an obscure class [1, 7].

1.1 DATA CLASSIFICATIONS

Actually, data classification is a very important subject, since data classification is the process of analyzing structured or unstructured data and organizing it into categories based on file type, contents, and other metadata. Data classification helps organizations answer necessary questions concerning their data which inform how they mitigate risk and manage data governance policies. Data types with similar levels of risk sensitivity are grouped together into data labels. Networks use four data classifications: unclassified, controlled, restricted, censored, and public information. Classification is a data extraction function that maps items in a collection to target classes or classes. The goal of classification is to accurately predict the target group for each case in the data. For example, a rating model can be used to identify loan applicants as low, medium, or high credit risk. Figure 1 displays an example of data classification scheme.

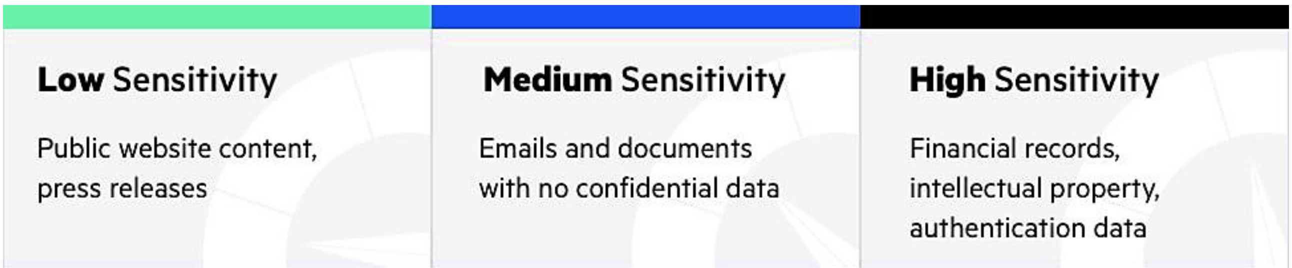

FIGURE 1. An example of data classification scheme [3].

1.2 CLASSIFICATION ALGORITHMS

Classification is commonly obtained by supervised learning but might also be achieved via unsupervised learning, e.g. where the category is not utilized or is unknown as in the ensemble technique. For the examine or test, we apply algorithms from the following methods: (1) Decision tree, (2) Rule extrapolation, (3) Clustering, (5) Artificial neural network (ANN), (6) Bayesian classifier and (6) Support vector machine. Classifiers' performance is usually computed by an accuracy scale. Such metric is evaluated by dividing the number of correctly categorized instances by the total amount of the instances. A properly classed instance is an instance in which the classifier expects the correct class for the test instance [7, 8]. Also by referring to [4–6, 9–11] we might locate the arrangement of the classification algorithms which are sorted according to the action quality as presented in Table 1.

As might be observed from Table 1, the best accuracy is achieved using the decision tree algorithm, which may be preferable to apply it to data classification. It also competes against the ANN algorithm in second place, which provides very close efficiency, as it is the preferred algorithm depending on the state and conditions of the data and the network.

Table 1. **Total Accuracy by Technique [8].**

Technique	Average accuracy
Decision Trees	$83,10%
Artificial Neural Networks	$82,85%
Rules	$82,76%
Clustering	$82,07%
Bayesian Classifiers	$81,76%
SVM	$74,72%

2. RELATED WORKS

In this section, we will introduce a survey of the utmost available articles along with relevant recent scientific studies concerning the subject of data classification using ANNs. The algorithm's learning rate, weight, bias, and initial parameter setting are the foundation of the neural network training method. It begins its leaning with a certain starting value, and the weight is updated with each iteration. The structure of a neural network is intricate and time-consuming to train. Such element made brain network less appropriate for order in information mining. It is possible to suggest a method for learning both the weight and the structure of the network. Weight adjustment in ANN is a combinatorial problem, and we must optimize the weight to achieve the desired output. The following are some approaches to ANN learning in various classification problems:

a) **Artificial neural network with back propagation** [11] suggests one variant of an ANN with BP for use in the classification of Landsat data. The neural network is trained with the back propagation algorithm. For multispectral image classification, another variant of ANN with BP is proposed in [7].The neural network is used to classify the image after the BP is trained on a traditional area of the image.

b) **Improved back propagation algorithm [8] Disc**uss the gradient delta rule-based neural network training with back propagation algorithm. It is very useful for architectures of parallel hardware. Instead of remaining constant, the momentum factor is determined with each step. Speed and convergence stability are better with improved BP than with conventional BP.

Some meta-heuristic algorithms in soft computing include the cuckoo search, firefly, genetic, and particle swarm optimization algorithms [12].Neural network training can benefit from these meta-heuristic algorithms. The meta-heuristic algorithms can be used in any field and yield approximate results. Where traditional algorithms produce a local optimum, these algorithms are used. Additionally, traditional algorithms consume more time to produce results and incur higher computational costs. To circumvent its limitations, numerous researchers used ANN in conjunction with these meta-heuristic algorithms in previous research. The following are examples:

1. **ANN with Particle Swarm Optimization (PSO)** A developmental framework which is a mix of structural advancement with weight learning, called PSONN, to work on the exhibition of fake brain networks was proposed in [13].In some structural methods, such as hill climbing, where the results are susceptible to becoming trapped at structure local optima, the initial network architecture determines the outcome. The hybrid method known as PSONN is utilized on two issues in the medical field: heart problems and breast cancer. [14] suggested a hybrid approach that combines the advantages of PSO and BP by utilizing the global searching capabilities of PSO and BP's local searching capabilities. Compared to BP, this hybrid method provides better classification accuracy and uses less CPU time. The iris classification issue is the focus of its application. [15] For fruit classification, a method that combined PSO, ABC, and a single hidden layer feed forward neural network was proposed..

2. **ANN with Genetic Algorithm (GA)$** [16]Present a brand-new hybrid neural network structure for the purpose of categorizing ECG beats. It is used to determine the number of nodes and their weight in the first layer of a neural network.$ [17]The land cover classification of remotely sensed data is demonstrated using a genetic algorithm and neural network in this paper. Back propagation and real coded GA hybrid are used. The neural network is optimized with genetic operators to prevent premature convergence. On GA, the BP algorithm is used to determine the initial connection weight.

3. **DNA microarray classification was proposed by ANN with Artificial Bee Col ony (ABC)** [18].ABC is used to reduce dimensionality and select the best set of genes for identifying specific diseases. These reduced genes are then used to teach ANN how to classify the DNA microarray. [19] Classify an MR brain image as normal or abnormal by utilizing a hybrid approach that combines improved ABC and forward neural network (FNN).Improved ABC, which is based on fitness scaling and chaotic theory, is used to optimize FNN parameters. [20] Train the neural network

for the classification problem in the medical field using the ABC algorithm. The crossover method is applied on nine different certifiable issue of clinical area..

4. **The improved cuckoo search was used to train the neural network in ANN with improved cuckoo search (ICS)** $ [21]The behavior of the cuckoo species, which lay their eggs in the nests of host species, serves as inspiration for the cuckoo search. In terms of parameters, improved cuckoo search differs from standard cuckoo search. To find an improved solution both globally and locally, the parameters pa and alpha are used. The algorithm's accuracy and convergent rate are improved as a result. The value of these parameters is fixed in the standard cuckoo search.

5. **Ant Colony Optimization (ACO) was used for ANN training** [22] to optimize the neural network's weight. It teaches the neural network how to classify patterns. [23] trained the ANN using a hybrid approach consisting of ACO and BP. Local optima are entrapped by back propagation (BP).Therefore, the global optimization algorithm will be utilized in this hybrid training to provide BP with good initial weight. These two methods are utilized for the classification of medical data : diabetes, heart, and cancer datasets..

6. **ANN with forbidden search** [35] Proposed a framework which half breed the four methods to be specific hereditary calculation reproduced tempering, unthinkable pursuit and back proliferation is utilized for brain network preparing. The uphill property of simulated annealing also exists (occasionally accepting bad moves). The parallel search characterizes GA. Flexible memory is a feature of tabu search. All of these aspects are combined in the proposed system. Four classification problems and one prediction problem are solved using the proposed method.

7. **ANN with GSA (gravitational inquiry streamlining)** [36] Propose an iris acknowledgment framework. It provides two half breed strategies FNNPSO and FNNGSA for iris characterization. It consists of four stages: using ANN, image acquisition, segmentation, normalization, and feature extraction are followed by classification. In order to train neural networks with optimal biases and weights, both PSO and GSA are utilized..

8. **ANN with biogeography-based optimization** [37] Provide a technique for classifying fruits based on their shape, color, and texture. The weight of the neural network is updated using an optimization algorithm based on biogeography.

9. **The proposed neural network model for a fuzzy logic control and decision sys tem is based on an ANN**. A neural network's training example might be utilized to construct a fuzzy and decision system, and a connectionist structure might be trained to develop a fuzzy logic rule and discover an input-output relationship.

3. METHODOLOGY

In order to implement the idea of the data classification using artificial neural networks (ANNs), the concept of ANN algorithm must be understood for data classification aspects. A weight is assigned to each connection in an ANN, which is a collection of connected input and output networks. One input layer, one or more intermediate layers, and one output layer make up the structure. The neural network learns by varying the weight of each connection. The network's performance is improved incrementally by updating the weight. ANN might be divided into two groups based on their connection: recurrent network and feed-forward network. A feed forward neural network is one in which unit-to-unit connections do not cycle, whereas a recurrent neural network does [10].The learning rule, the architecture, and the transfer function all have an impact on the behavior of a neural network. The weighted sum of the input triggers the activation of neural network neurons. A single neuron output is produced when the activation signal is transmitted through the transfer function. This transfer function results in a nonlinear network. The interconnection weight is improved during training until the network achieves the desired level of accuracy. It is useful in a variety of applications, including pattern recognition [2], medical [2, 24], business applications [3], [3], pharmaceutical science [4], bankruptcy application [9], and speech recognition [5, 6]. It has several advantages, such as parallelism, less affected by noise, and good learning ability [10]. Compatibility, tolerance for noisy data, parallelism, and the ability to learn from examples are among the neural network's most appealing features. The network's speed is increased by parallelism. However, in addition to these benefits, it has numerous drawbacks. First, neural network training is expensive and time-consuming. The accuracy of a classification is significantly impacted by the training of a neural network. There are numerous algorithms for neural network training [11].It has been argued that neural networks lack interpretability. For instance, it is challenging for humans to decipher the symbolic meanings of the network's "hidden units" and learned weights.

3.1 ANN STRUCTURE

The neurons utilized in the ANN algorithm are numeric amounts. It is represented as a model of biological neurons. Formal neurons might be thought of as primitive units in a pseudo-neural network. The shown graph deals with the general numerical model of formal neurons [19] and as shown in Figure 2:

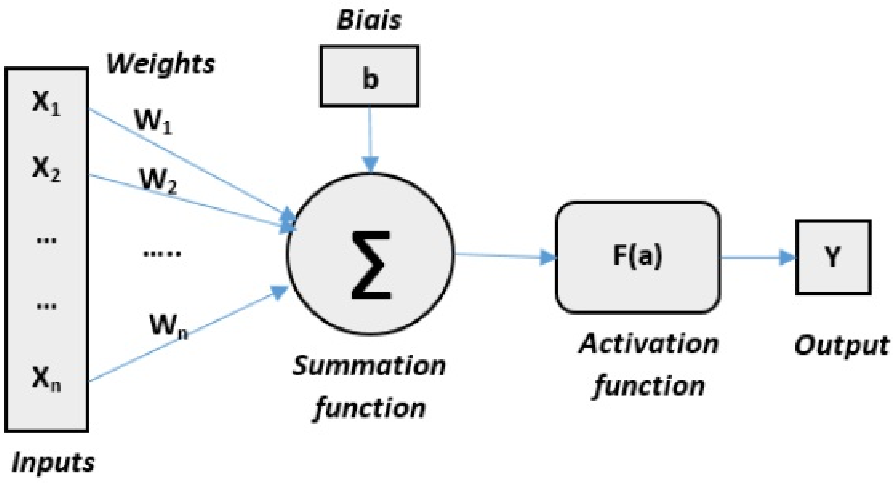

FIGURE 2. Numerical structure of the formal neuron.

The formal neuron which is illustrated in the above figure has n inputs indicated as $\{X_1,X_2,\ldots,X_n\}$. Every line which interfaces such contributions to the addition intersection is allocated a weight signified as $\{W_1,W_2,\ldots,W_n\}$. The net info *yin* can be determined as follows:

$$yin = x1.w1 + x2.w2 + x3.w3 + \ldots + xn .wn + b \tag{1}$$

The improveimg function *F(a)* is part of the essential pieces of a neuron. A little initiation capacities might be thought of (limit work, direct capacity, sigmoid capacity . . .). In this study, we have picked a sigmoid function as presented in Figure 3, for its nonlinearity which composes it conceivable to inexact either capacity. Finally, the resulting **y** of the neuron is provided in the accompanying recipe:

$$y = F(y_{in})\sum w_i * x_i + b \tag{2}$$

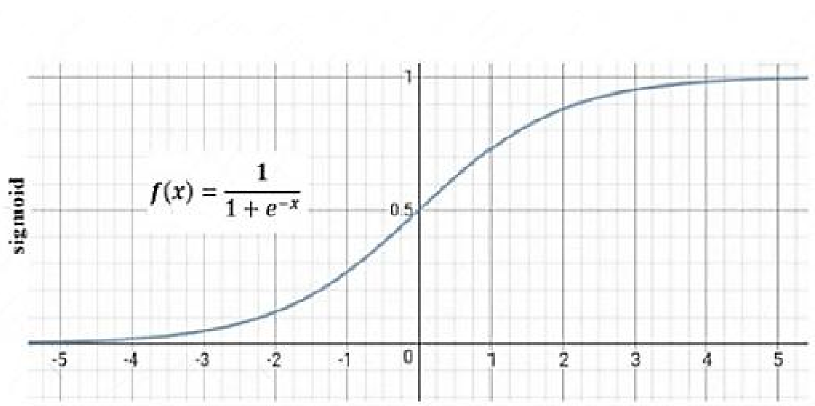

FIGURE 3. the sigmoid function illustration.

3.2 MULTI-LAYER PERCEPTRON

The multi-facet perceptron (MLP) displayed in Figure 4 is a class of feed-forward fake neural network that has somewhere around three layers of hubs. It creates a bunch of yields $\{y_1, y_2, \ldots, y_n\}$ from a bunch of data sources $\{X_1, X_2, \ldots, X_n\}$. With the exception of the info hubs, every hub is a neuron that utilizes a nonlinear initiation work [21–23].

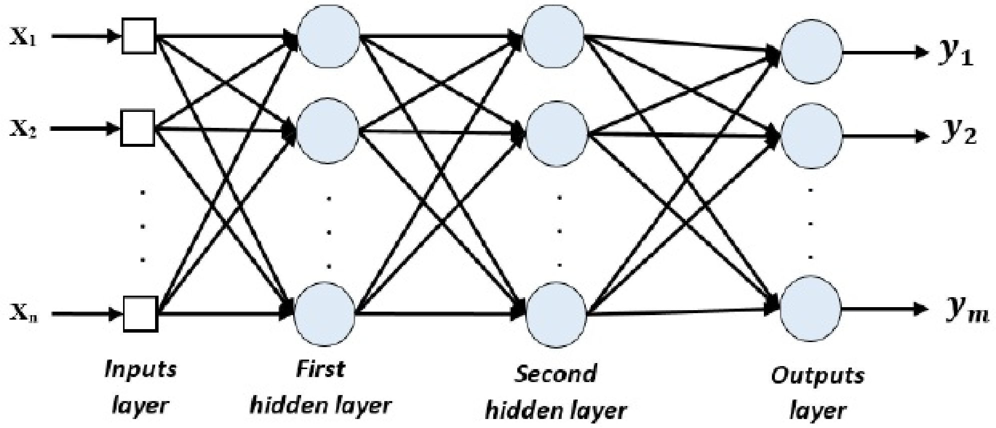

FIGURE 4. **Block diagram of MLP scheme.**

A neural network is prepared with info and target pair designs with the capacity of learning. MLP can isolate information that isn't directly recognizable [20]. It is particularly prepared utilizing a supervised learning technique got back to propagation (BP) algorithm [21], which targets limiting the worldwide mistake estimated at the yield layer by the connection howl:

$$e(t) = yd\ (t) - ym\ (t) \tag{3}$$

Where *yd(t)* signifies the ideal output, and *ym* (*t*) the deliberate yield of the neuron.

The BP algorithm utilizes an iterative supervised learning system, where the MLP is prepared with a bunch of predefined sources of info and yields. The worldwide mistake *Eg* (*t*) is determined by equation (4), this blunder can be limited by the gradient descent technique [22].

$$E_g(t) = \frac{1}{2}\sum_{i=1}^{n}(y_{d,i}(t) - y_{m,i}(t))^2 \tag{4}$$

There are a few preparing algorithms that might become utilized to train a MLP network. In this study, we will present a subjective examination between two preparing algorithms: semi newton and form slope. Wherein the pre-owned preparing capacities are separately train-lm: (Levenberg Marquardt (LM)) and train-scg (Scaled Conjugate Gradient (SCG)).

3.3 THE PROPOSED DATA CLASSIFICATION WITH ANN ALGORITHM

The operation of the proposed structure will be implemented using data set from www//http//kaggle.com web site, representing medical data having information of mixed medicine cancer cases for a medicine health center. These mixed data are various type of cancer cases with different levels of importance according to the patient case. Such data sets will be entered to the designed ANN algorithm in order to classify them according to their importance. The block diagram of the suggested model is shown in Figure 5.

Also, the flowchart of the proposed data classification along ANN algorithm has been illustrated in Figure 6.

The data set will be entered to the first ANN layer to be prepared for analysis. The data are normalized, then the network structure will be selected according to the design (backpropagation neural network method, the BPNN supported with Levenberg Marqurdte (LM) activation function). Next, the ANN weights and their basis will be normalized. The entered data will be trained and tested according to the designed ANN settings. After that, the resulting response will compared with the required targits, if the error still high, the process will be repeated untill reaching to the acceptable error. Hence the weights and basis will be recorded and the program will be terminated.

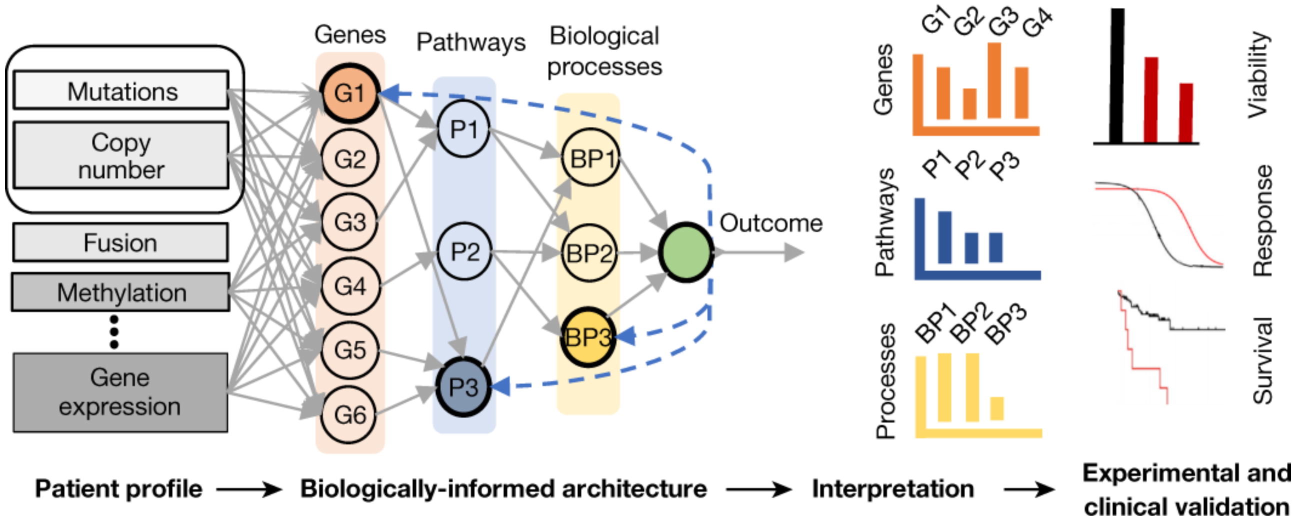

FIGURE 5. **The block diagram of the suggested model.**

4. SIMULATION RESULTS

The proposed structure has been implemented and examined successfully utilizing MatLab2020 simulation program, m. files. This software, will employ the ANN algorithm upon entered-packets data samples. The suggested scheme design requirements are tabulated in table 2.

ANN algorithm Details	Cancer Data Size	Input Layer	Hidden Layer	Output Layer
	9× 699	**9**	**50**	**2**

The designed ANN algorithm with backpropagation neural network method, the BPNN supported with Levenberg Marqurdte (LM) activation function is presented in Figure 7.

The program has been implemented according to the entered cancer cases data sets, and the resulting performances of the ANN algorithm training are illustrated in the incomming figures.

From the above figure, it is obvious that, the best validation performance of the mean square erroe (MSE) has been achieved with 0.0437 at epoche of 13. Next, the confusion matrix has been obtained and displayed in Figure 9.

By referring to Figure 9, the confusion matrix of our implemented data classification against ANN algorithm has shown a very high matching among the resulting class with the targit class with 97.3% matching and onlt 2.7% missmatch. Also, the gradient and the validation fall results have been illustrated in Figure 10.

A very good gradient value of 0.011564 with validation check of 6 at epoche 19 those ensuring the excellent performance of the examination program. Furthermore, the error histogram of the algorithm has been displayed in Figure 11.

Moreover, the error performance of the examination program showing an excellent performance for the trained, validated, and tested instances, with 0.04957 error amount. Finally, the receiver operating characteristic curves have been shown in Figure 12.

At last, the ROC curves of the implemented ANN algorithm presenting a perfect matching among true with false posetive rates for the trained, validated, tested, and all cases. This indicates that the examined cancer data have been perfectly matched with the required classes. Now, the plot of the entered cancer data set have been illustrated in Figure 13. The figure shows the connections among the training set with the target data values for each input data value which have been indicated with blue colour. Also, the plot of the obtained classified cancer data set have been presented in Figure 14. Similarly, the figure shows the connections among the validation set with the validation data values for each input data value which have been indicated with red colour.

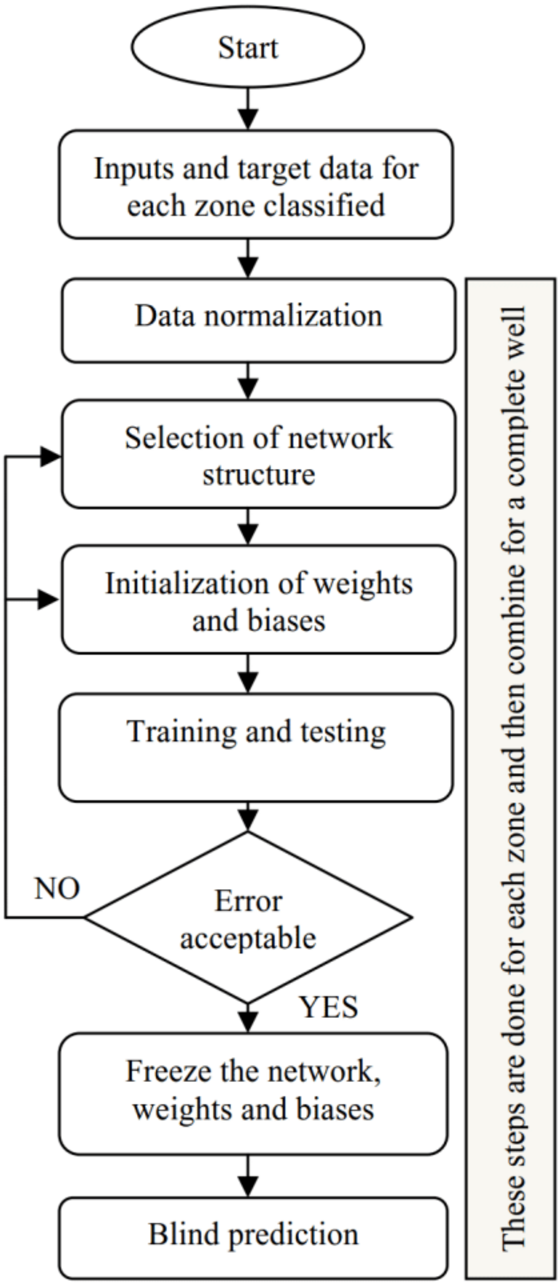

FIGURE 6. **the flowchart of the proposed data classification along ANN algorithm.**

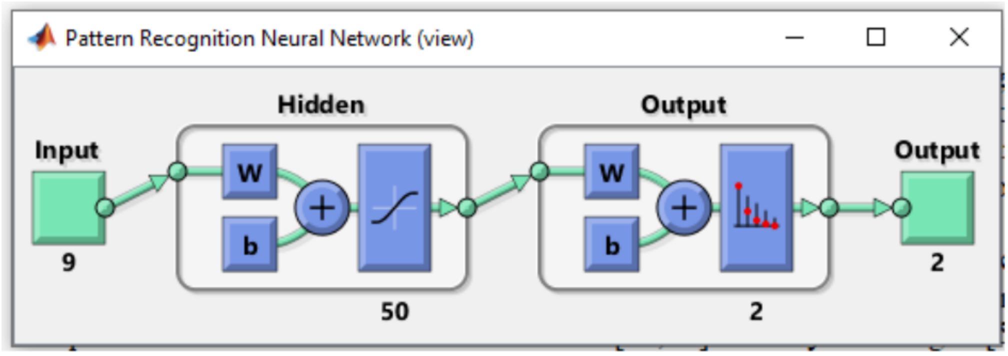

FIGURE 7. Structure of the ANN architecture [8].

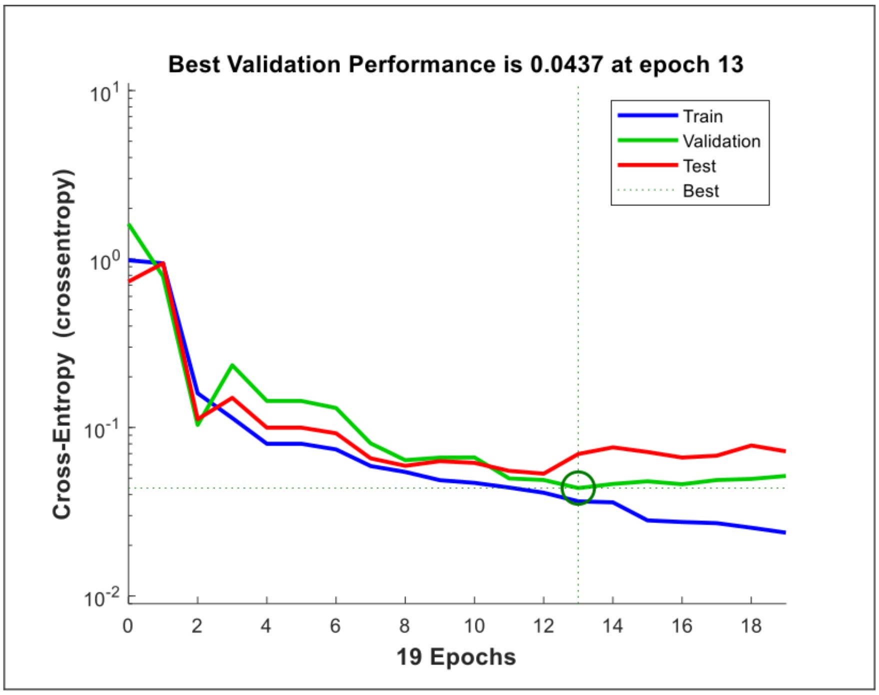

FIGURE 8. Eroor performance of the ANN architecture algorithm examination.

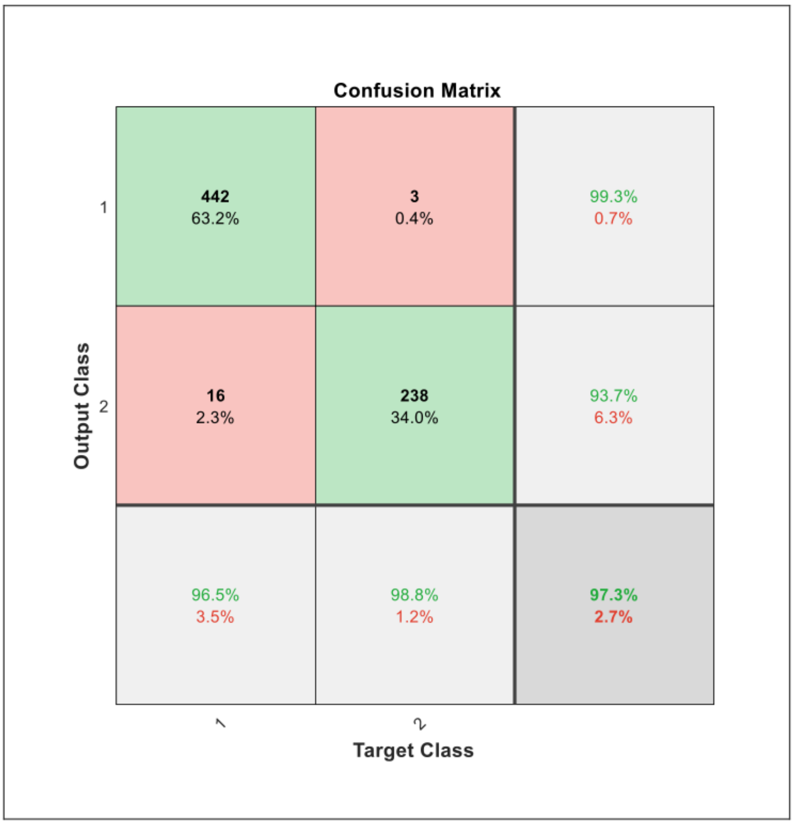

FIGURE 9. The confusion matrix.

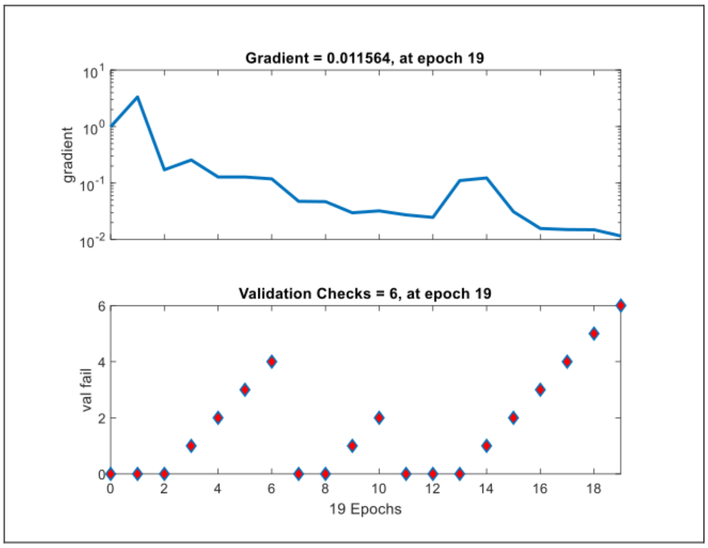

FIGURE 10. The gradient and the validation fall results.

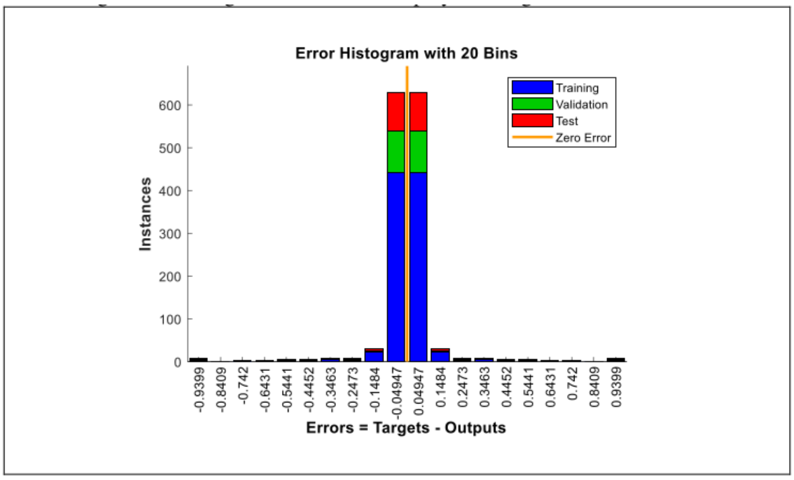

FIGURE 11. **Error histogram of the ANN algorithm.**

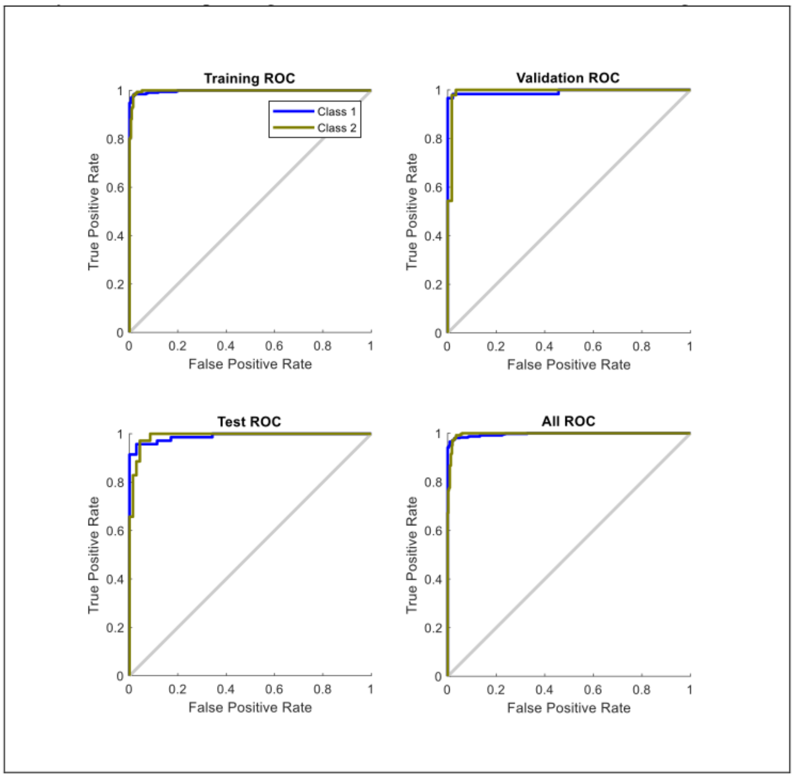

FIGURE 12. **The receiver operating characteristic curves.**

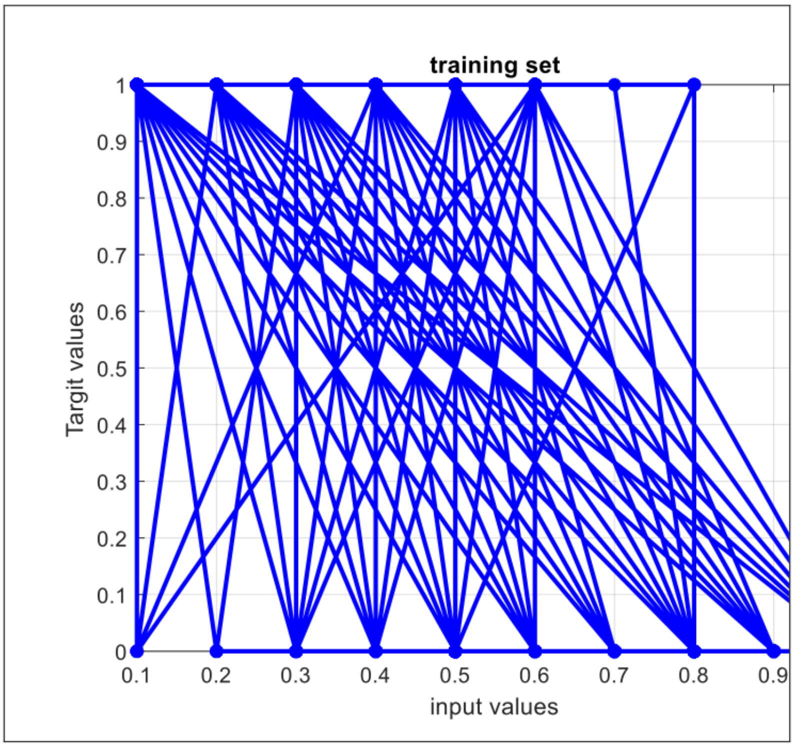

FIGURE 13. **The plot of the entered cancer data set.**

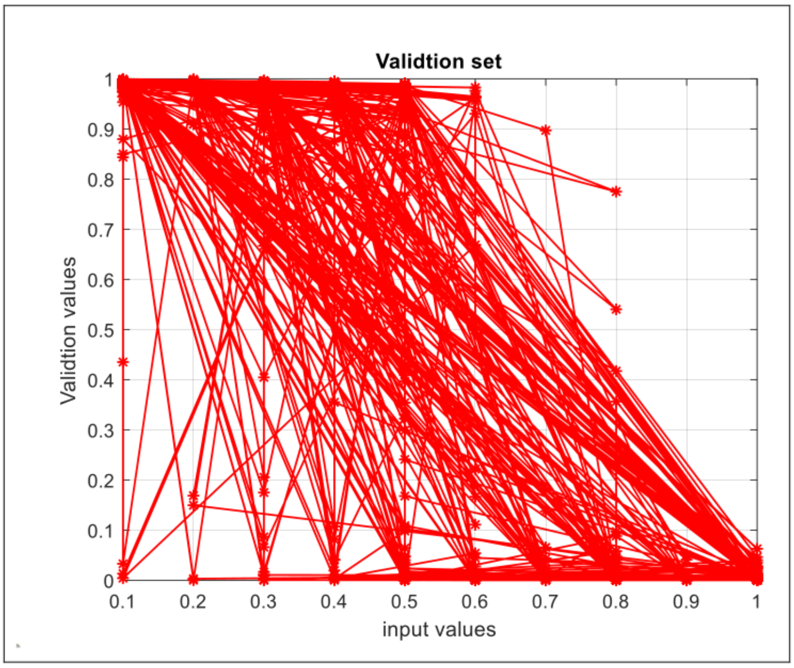

FIGURE 14. **The plot of the obtained classified cancer data set.**

5. CONCLUSIONS

Artificial neural network (ANN) classification is one of the most recent classification techniques. It is regarded as one of the most dynamic and current areas of application-related research. A subfield of artificial intelligence (AI) is ANN. The backpropagation algorithm is used to train the neural network. Back propagation neural university (BPNN) with Levenberg Marqurdte (LM) activation function might be applied as a successful data classification tool with the right set of training and learning functions that work at maximum likelihood. In this study, the validity of such functions for cancer based datasets was examined, as was the effect of various combinations of functions when using ANN as a file classifier. The BPNN supported by Levenberg Marqurdte (LM) activation function was more accurate than the maximum likelihood method when compared to the backpropagation neural network approach. It is possible to have a high predictive ability against BPNN that is stable and operates well. For cancer data classification, the multilayer feed-forward neural network algorithm is also utilized. The Levenberg Marqurdte (LM) activation function-supported BPNN, on the other hand, outperforms other classification algorithms. The obtained results were very good with the best validation performance of the mean square erroe (MSE) of 0.0437 at epoche of 13. Also, the confusion matrix of our implemented data classification against ANN algorithm has shown a very high matching among the resulting class against the targit class with 97.3% matching and onlt 2.7% missmatch. Furthermore, the ROC curves of the implemented ANN algorithm presenting a perfect matching among true with false posetive rates for the trained, validated, tested, and all cases. This indicates that the examined cancer data have been perfectly matched with the required classes.

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CONFLICTS OF INTEREST

The author declares no conflict of interest.

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