Comparison between Back-propagation and General Regression Neural Networks for Underwater Mine detection

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***Abstract*—Detection of remote targets is a very active research domain of Pattern Recognition and Neural Networks in the field of Defense. Researchers and scientists are continuously striving to achieve the objective of high accuracy and low rate of false alarms in order to improve their Target Recognition Systems. When we consider the requirements of defense organizations in the domain of Target Recognition, it can be stated that their needs are very specific. They know what they are looking for. They have all the details of the Target but they rarely know when they will encounter that target. Therefore, they require very accurate systems to ensure the security is not breached. This is where the Neural Networks for efficient Target Recognition comes into play.**

Neural Networks are considered one of the most competent techniques in the applications regarding Decision Making, Pattern Recognition, and Target Detection etc. Target Detection and Recognition plays an important role in maintaining security at borders, harbors and coastal areas. It is not only important to detect the targets which are on land or in the air but it's also very crucial to monitor shallow waters for any undersea enemy vehicle or mines. Therefore, the process of Target Recognition has to be very efficient in order to cater the above complications. Neural Networks have shown some promising results where computing large data in real-time environment is required. They can efficiently perform the classification of targets buried in noisy, cluster rich incoming signals.

This paper is produced in order to analyze two different Neural Networks and their precision when they both encounter same targets in similar environment. The analysis is done on Feed Forward Back Propagation Neural Network (FFBP-NN) and General Regression Neural Network (GRNN) with SONAR dataset and then a conclusion is formed on the basis of their performance and efficiency.

Keywords: Pattern Recognition, Target Recognition, Classification, Neural Networks.

I. INTRODUCTION

Underwater object detection is a crucial aspect of a naval vessel especially submarines. SONAR is the primary system used for underwater target and object detection. The submarines main weapon is stealth and thus it has to remain submerged below the water level maintaining a certain depth. The sonar uses sound waves or collectively ultrasonic waves to detect any object in the water. In shallow waters near the coasts minefields are present and some rocks so the submarine must be able to classify them in time to avoid any disaster.

Artificial intelligence during the last two decades has opened new prospects for the modern research era. Numerous fields like signal processing, image processing, bioinformatics, defense applications, power, space exploration, weather predictions and financial forecasting etc [1].

Artificial intelligent systems are also termed as classifiers. The most notorious and widely used classifiers are neural networks, decision trees, genetic algorithms, expert systems etc. [2]

This paper focuses solely on neural networks. A Neural Network is basically a statistical computational model of the human biological nervous system [2]. The techniques of neural networks in defense systems are not that old and it was incorporated in the late 1980's. The primary field of interest then and now is target detection and recognition. As in modern defense arsenal, numerous new tools such as ballistic and cruise missiles, state of the art fighter planes, nuclear submarines etc pose serious threat to the well being of a country. It is imperative that these threats be detected at the earliest so counterattacks and countermeasures are deployed. In such cases neural networks are being used together with numerous pattern recognition and machine learning methods to get the highest accuracy possible [3], [4].

The reason for using neural networks is because of their flexibility and there tendency to predict, classify all sorts of data better than any other classifier.

Neural networks are basically classified in to two categories,

Feed-Forward Neural Networks

Recurrent (or Feedback) Neural Network

Our dataset classification problem exhibits outputs at two levels; such problems are termed as binary classification problems. And for such cases the feed-forward neural networks are more viable. In feed-forward networks we have used the Feed-forward Backpropagation Neural Network [5]. In addition to BPNN the General Regression Neural network is also being used to give a comparative analysis. The dataset used for the paper is the sonar dataset taken from the UCI repository of Machine Learning [6].

This paper is organized as follows. Section I gives an account of the preliminaries, Section III briefly describes the Feed-forward Neural Network and the General Regression Neural Network. The dataset is described in Section IV. Section V gives the Simulations and results. Finally, Section VI gives conclusions.

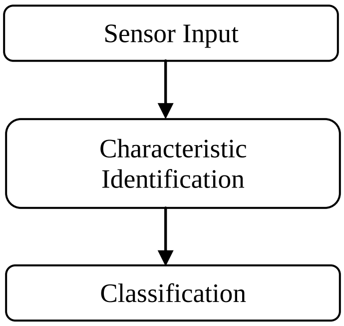

Figure 1. Basic Target Recognition Block Diagram

II. PRELIMINARIES

A. Object Recognition

Object recognition is the task of finding an object present in some data. The data can be a numeric matrix or vector based data or it could be an image.

B. Target Recognition

Recognition of target or object from a specified data taken from any device such as a sensor is called Target Recognition.

Target Recognition involves characteristic extraction from the given data and its classification. A basic Target Recognition diagram is shown in "Fig. 1".

C. Classification

Classification is the categorization of entities, objects or patterns in to specific classes or groups depending on their similarities and characteristics.

The most widely used classifiers are decision trees, support vector machines (SVMs), perceptrons, neural networks, k-nearest neighbor classifiers, and radial basis function classifiers.

The performance of a classifier depends immensely on the characteristics of the data to be classified. There is no single classifier that works best on all given problems. Classifier performances have been compared by various empirical tests and to find the characteristics of data that determine classifier performance. Determining an ideal classifier for a given problem is however still more an art than a science.

III. NEURAL NETWORKS

Neural networks are mathematical and computational equivalent model of biological neural network. The model is rough, as the human brain has very parallel computational device, achieving great power due to connectivity of billions of simple neurons. The technology is far from the point where a machine would be able to attain the complexity of the human brain. Neural Networks have unlimited applications in fields like signal processing image and video processing, weather forecasting, stock market predictions, genetics, bioinformatics, power systems, defense systems etc.

A. Feed-Forward Backpropagation Neural Network (FF-BPNN)

Backpropagation Neural Network is a network that based on Backpropagation learning technique and that works on the principle of supervised learning [7]. In general it is called the Feed Forward Backpropagation neural network. With regard to architecture it is basically a Multi-layer Perceptron [8]. The Backpropagation neural network is the gemstone that enchanted and mesmerized researchers and showed the true power of neural networks. It opened research doors with endless opportunities in various fields of engineering, sciences and statistics while being computationally economical. But on the darker side the BPNN has also been called the 'black box' as it has a fixed algorithmic operation and that's about it, there is no fixed topology (number of nodes and neurons used) for it and exhibits different results with different data subsets of the same dataset that is it is very hard to sway it to global minima. Regardless of all these factors, overall the BPNN is quite accurate and easy to manipulate with respect to other neural networks.

Steps involved in working of BPNN

- The dataset instances are mixed to provide most generalized results.
- The dataset is divided in to two parts; the training and the testing datasets.
- The training dataset comprises of about 70% of the original dataset and the testing dataset occupies about 30%.
- Now the neural network is trained on known target value (in our case binary).
- After the BPNN has been trained, the testing dataset that the neural network has never seen is applied to check the accuracy of the classification.

"Fig. 2" shows a basic BPNN comprising of an input, hidden and output layer.

Where a_1, a_2 and a_n are the inputs applied on the input layer, n1 is the hidden layer and n2 is the output layer. The output of the network is 'y'. 'δout' is the error signal that is generated when the output 'y' is compared to the target output of the training dataset comprising of the ideal classification result.

The error signal moves from the output layer to the hidden layer changing the weights to adjust to the correct result once this error is minimized close to zero the weights are fixed meaning the network is trained and can be tested.

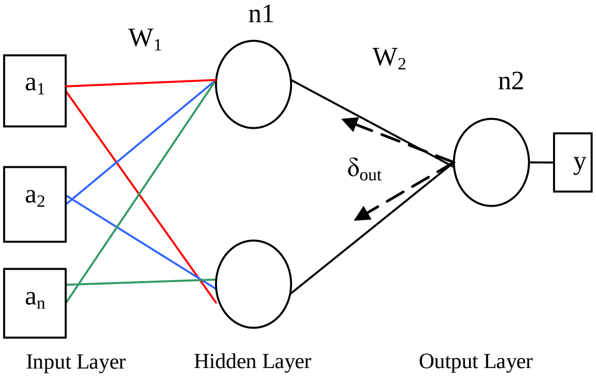

Figure 2. Simple Back Propagation Neural Network

B. General Regression Neural Network (GRNN)

The General Regression Neural Network (GRNN) is one of the most popular neural networks. They have a parallel structure where the learning is one fold that is input to structure to output there is no iterative learning present such as in the case of Multi Layer Perceptrons (MLP) making them fast to some extents. Also GRNN performs well on noisy data than Backpropagation Neural Networks (BPNN) if the available data is large enough. This is one of the reasons the GRNN is being used in target recognition, predictive and diagnostics problems because a lot of noisy data is present is such cases.

GRNN is also very unswerving and as the size of the dataset increases the error approaches towards zero. The GRNN works quite accurately with light datasets.

The GRNN infrastructure consists of four layers input, hidden, summation and output layer.

- The input layer merely transports the data attributes to the next layer in a parallel archetype.
- The second layer consists of all the training samples.
- In the summation layer the summation units or neurons perform a dot product on the attributes of the weight vector of the second layer.
- Then in the output layer the respective local outputs are divided to get the predictions.

Steps involved in working of GRNN

- Same steps as the BPNN are adopted other then calculating spread constant that in the case of SONAR dataset is 0.06.

GRNN is used for under water mine detection using SONAR dataset whose results are shown in Section V.

The following fig shows a basic GRNN comprising of an input, hidden, summation and output layer.

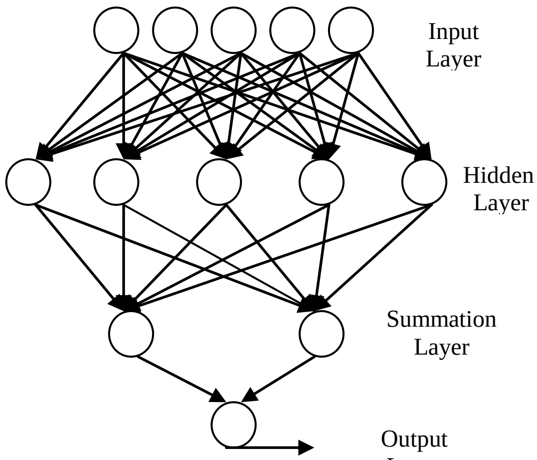

Figure 3. Simple GRNN

IV. Description of Dataset

The sonar dataset is taken from the UCI Machine Learning repository. The sonar dataset comprises of 208 vectors having 60 attributes or it can be said that the data is 60 dimensional where each value signifies the strength of the signal at a particular frequency over a span of time. These frequencies increase in a manner that the last value is taken at highest frequency. The first 97 vectors represent rocks at different aspect angle attained by bouncing sonar signals from rough rock surface. Next 111 vectors are Mines attained at different aspect angles by bouncing sonar signals over a metallic cylinder. In the data mines are represented by 0's and rocks by 1's.

The goal is to classify rocks and mines as accurately as possible using the BPNN and GRNN.

V. Simulations & Results

MATLAB 2007a is used for simulations and results. The procedure used for the classification is shown in "Fig. 4".

The considered sonar dataset distribution is shown in Table I. About 70% of the dataset is taken as training data.

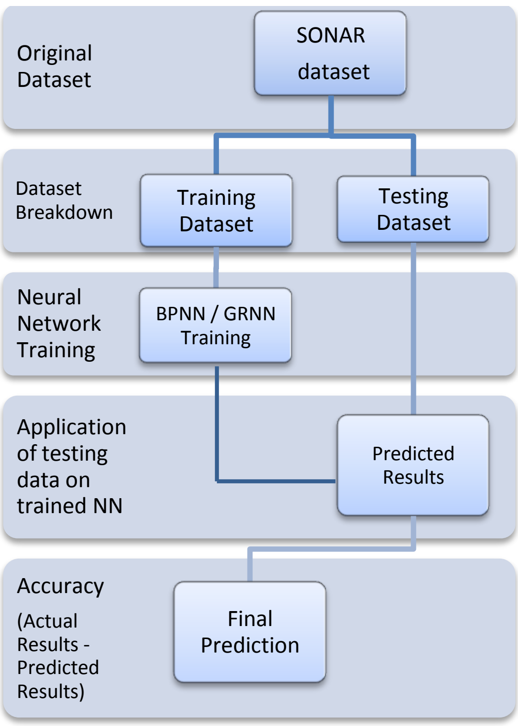

Figure 4. Block diagram of NN Application

TABLE I.
Sonar Data Distribution

Overall Data (208)		Training Data (146)		Testing Data (62)	
Rocks	Mines	Rocks	Mines	Rocks	Mines
97	111	66	80	30	32

The data distribution is not fixed, that is why different researchers get different results and thus accuracy varies.

Also the ability of a neural network to classify accurately depends on the class distribution of respective data that is it depends upon how much the classes of a dataset overlap.

A. BPNN applied to Sonar dataset

The sonar dataset was trained in matlab using the neural network toolbox. The following fig shows the BPNN training performance with error close to '0' as shown in "Fig. 5".

Stem plot for misclassifications of mines is plotted in "Fig. 6". The classification accuracy of SONAR dataset using BPNN is shown in Table II.

B. GRNN applied to Sonar dataset

GRNN was applied to SONAR dataset in similar manner as BPNN with exceptions to various options due to difference in architecture of the two.

"Fig. 7" shows the stem plot for the misclassification of mines. The classification accuracy of SONAR dataset using GRNN is shown in Table III.

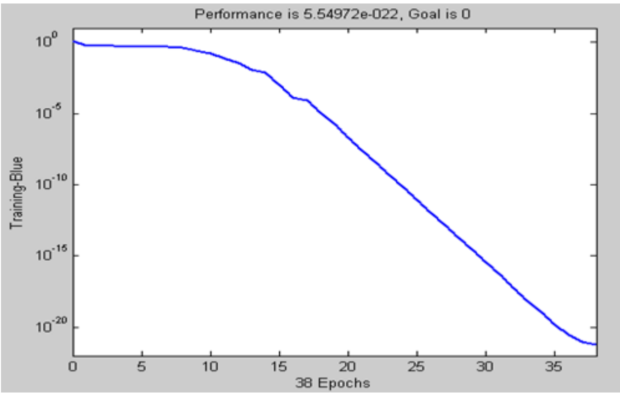

Figure 5. BPNN training performance

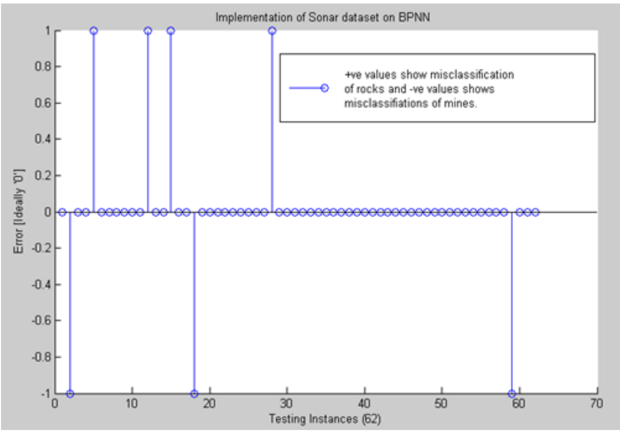

Figure 6. Stem graph showing misclassification (BPNN)

TABLE II.
BPNN CLASSIFICATION ACCURACY

Accuracy of mine classification	90.62%
Accuracy of rock classification	86.67%
Overall dataset accuracy	88.709%

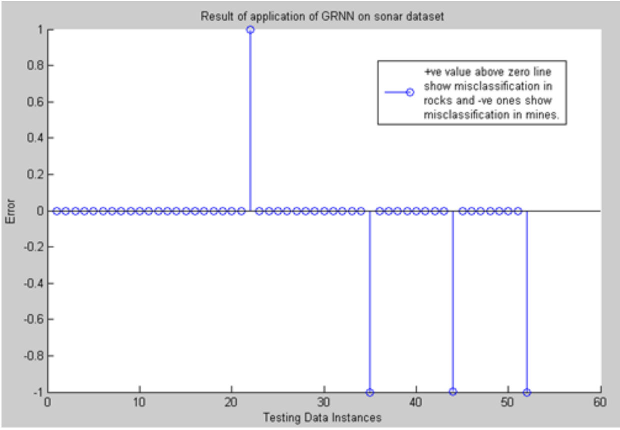

Figure 7. Stem graph showing misclassification (GRNN)

TABLE III.
BPNN CLASSIFICATION ACCURACY

Accuracy of mine classification	90%
Accuracy of rock classification	95.45%
Overall dataset accuracy	92.3%

VI. CONCLUSION

The BPNN showed very promising results as shown in Section V. Still there are some issues that must be pointed out such as the BPNN exhibits slow learning for big datasets, like this may be due to the iterative learning used by BPNN. The choice of topology that the number of neurons used in various layers of BPNN drastically affects the prediction and classification capability of the NN. If too many neurons are used for BPNN training the NN can attain good learning performance but that does not ensure accurate and good generalization. Last, the BPNN gets stuck on the local minima and it is almost impossible to get global minima. Still it is very effective and unlike most of the neural networks which produce good results for some datasets and bad for others, BPNN performs fairly well on most of them.

GRNN on the other hand is more accurate as it is non-iterative, highly parallel and takes less time during the training and testing phase.

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