

## **CLASSIFICATION OF SONAR IMAGES USING MULTILAYER PERCEPTRON NEURAL NETWORK**

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**Abstract—** In this paper another characterization calculation is proposed for the Classification of five sort of Side scan Sonar images. So as to create calculation 83 Side scan Sonar images have been viewed as, With a view to extricate highlights from the Side scan Sonar images after picture handling, a calculation proposes FFT changed coefficients. The Efficient classifiers in view of Multilayer Perceptron (MLP) Neural Network. A different Cross-Validation dataset is utilized for appropriate assessment of the proposed characterization calculation as for imperative execution measures, for example, MSE and order precision. The Average Classification Accuracy of MLP Neural Network containing one concealed layers with 13 PE's sorted out in a run of the mill topology is observed to be predominant (88.33 %) for Training and cross-approval. At long last, ideal calculation has been produced based on the best classifier execution. The calculation will give a powerful option in contrast to conventional strategy for Side output Sonar pictures examination for Classify the five kind of Side scan Sonar images in sea.

**Keywords—** MatLab, Neuro Solution Software, Microsoft excel, Fast Fourier Transform Techniques

### **I. INTRODUCTION**

A standout amongst the most prevalent instrument for submerged looks into is Side Scan Sonars [1],[2],[3]. Side Scan Sonars are utilized to make a picture of ocean bottom to give a comprehension of the distinctions in material and surface kind of the seabed by utilizing acoustic impressions of pulses. Sometimes, these pictures can't give a proficient data to analysts and researchers to effortlessly remember them. They are for the most part in grayscale or in two hues, and extra commotion, for example, profundity and water contamination of ocean depths diminish the quality and perceivability of sonar pictures. In any case, notwithstanding every one of these hindrances, scientists are as yet performing investigations and examinations to find and perceive the profundity of the seas.

Notwithstanding, order or acknowledgment of the articles that show up in these pictures is troublesome assignment and necessities human experience. In any case, in the event that we consider the measure of the region that is secured by the seas, it is more viable to give programmed insightful acknowledgment or arrangement that mimics human experience. Sonar Image Classification System was produced to mimic human experience by grouping sonar pictures, on the off chance that they are human made wreck or characteristic submerged shapes. Precedents of Human-Made wrecks and Natural Shapes can be found in Figure 1.

We will take an information Side output Sonar pictures and concentrate the highlights of pictures. We will utilize Artificial Neural Network as our classifier for examination of Side sweep Sonar pictures. A counterfeit neural system (ANN), as a rule called neural system (NN), is a scientific model or computational model that is enlivened by the structure as well as utilitarian parts of organic neural systems. Contingent upon the applications, numerous frameworks have been proposed to understand or if nothing else to lessen the issues, by making utilization of picture preparing, design acknowledgment and some programmed arrangement instruments. .

The dependability and the achievement of these frameworks are rely upon the adequacy of connected information pre-handling methods and neural systems which can be utilized for effective demonstrating of human's visual framework amid the acknowledgment or arrangement of examples. Neural systems have an imperative part in the demonstrating of human experience and basic leadership process into PCs.



(a)

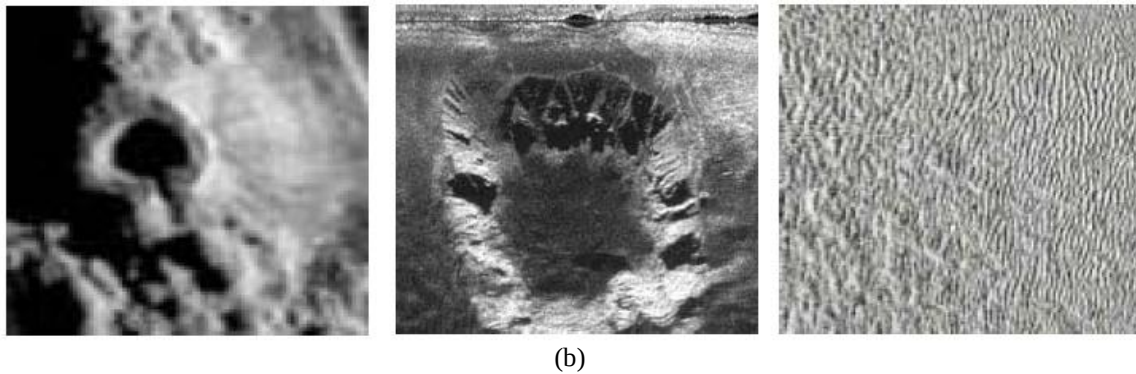


Figure1 : Sample Test Images (a) Human-Made Wrecks and (b) Natural Underwater Shapes

## II. RESEARCH METHODOLOGY

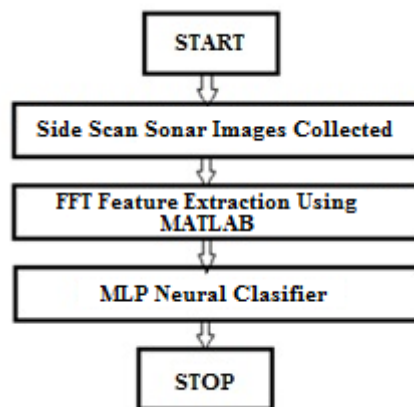


Figure2.1 Methodology of work

It is characterization of Side scan Sonar images Using Neural Network Approaches.. Information procurement for the proposed classifier intended for the order of Side scan Sonar images. The most essential un related highlights and in addition coefficient from the images will be removed .keeping in mind the end goal to separate highlights FFT changed area will be utilized.

### 1) Neural Networks

**Following Neural Networks are tested:**

#### Multilayer perceptron (MLP)

The most widely recognized neural system show is the multi layer perceptron (MLP). This sort of neural system is known as an administered arrange in light of the fact that it requires a coveted yield with a specific end goal to learn. The objective of this sort of system is to make a model that accurately maps the contribution to the yield utilizing authentic information with the goal that the model would then be able to be utilized to create the yield when the coveted yield is obscure. A graphical portrayal of a MLP is demonstrated as follows:

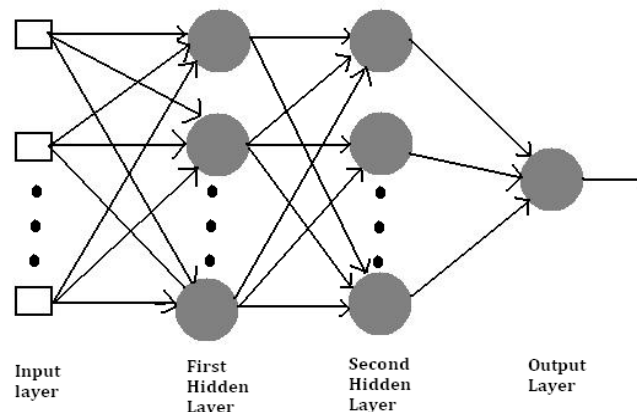


Figure 2.2: The Structure Of Neural Network Model MLP.

The MLP and many other neural networks learn using an algorithm called back-propagation. With back-propagation, the input data is repeatedly presented to the neural network. With each presentation the output of the neural network is compared to the desired output and an error is computed. This error is then fed back (back-propagated) to the neural

network and used to adjust the weights such that the error decreases with each iteration and the neural model gets closer and closer to producing the desired output. This process is known as "training".

❖ **Learning Rules used:**  
 ➤ **Momentum**

Momentum simply adds a fraction  $m$  of the previous weight update to the current one. The momentum parameter is used to prevent the system from converging to a local minimum or saddle point. A high momentum parameter can also help to increase the speed of convergence of the system. However, setting the momentum parameter too high can create a risk of overshooting the minimum, which can cause the system to become unstable. A momentum coefficient that is too low cannot reliably avoid local minima, and can also slow down the training of the system.

➤ **Conjugate Gradient**

CG is the most popular iterative method for solving large systems of linear equations. CG is effective for systems of the form  $Ax=b$  (1) where  $x$  is an unknown vector,  $b$  is a known vector, and  $A$  is a known, square, symmetric, positive-definite (or positive-indefinite) matrix. (Don't worry if you've forgotten what "positive-definite" means; we shall review it.) These systems arise in many important settings, such as finite difference and finite element methods for solving partial differential equations, structural analysis, circuit analysis, and math homework.

Developed by Widrow and Hoff, the delta rule, also called the Least Mean Square (LMS) method, is one of the most commonly used learning rules. For a given input vector, the output vector is compared to the correct answer. If the difference is zero, no learning takes place; otherwise, the weights are adjusted to reduce this difference. The change in weight from  $u_i$  to  $u_j$  is given by:  $\Delta w_{ij} = r \cdot a_i \cdot e_j$ , where  $r$  is the learning rate,  $a_i$  represents the activation of  $u_i$  and  $e_j$  is the difference between the expected output and the actual output of  $u_j$ . If the set of input patterns form a linearly independent set then arbitrary associations can be learned using the delta rule.

It has been shown that for networks with linear activation functions and with no hidden units (hidden units are found in networks with more than two layers), the error squared vs. the weight graph is a paraboloid in  $n$ -space. Since the proportionality constant is negative, the graph of such a function is concave upward and has a minimum value. The vertex of this paraboloid represents the point where the error is minimized. The weight vector corresponding to this point is then the ideal weight vector.

➤ **Quick propagation**

Quick propagation (Quickprop) [1] is one of the most effective and widely used adaptive learning rules. There is only one global parameter making a significant contribution to the result, the  $\epsilon$ -parameter. Quick-propagation uses a set of heuristics to optimise Back-propagation, the condition where  $\epsilon$  is used is when the sign for the current slope and previous slope for the weight is the same.

➤ **Delta by Delta**

Developed by Widrow and Hoff, the delta rule, also called the Least Mean Square (LMS) method, is one of the most commonly used learning rules. For a given input vector, the output vector is compared to the correct answer. If the difference is zero, no learning takes place; otherwise, the weights are adjusted to reduce this difference. The change in weight from  $u_i$  to  $u_j$  is given by:  $\Delta w_{ij} = r \cdot a_i \cdot e_j$ , where  $r$  is the learning rate,  $a_i$  represents the activation of  $u_i$  and  $e_j$  is the difference between the expected output and the actual output of  $u_j$ . If the set of input patterns form a linearly independent set then arbitrary associations can be learned using the delta rule.

It has been shown that for networks with linear activation functions and with no hidden units (hidden units are found in networks with more than two layers), the error squared vs. the weight graph is a paraboloid in  $n$ -space. Since the proportionality constant is negative, the graph of such a function is concave upward and has a minimum value. The vertex of this paraboloid represents the point where the error is minimized. The weight vector corresponding to this point is then the ideal weight vector. [10]

### III. SIMULATION RESULTS

#### 1) Computer Simulation

The MLP neural system has been simulated for 83 distinct images of side scan sonar images out of which 63 were utilized for preparing retrain and 20 were utilized for cross approval.

The simulation of best classifier along with the confusion matrix is shown below :

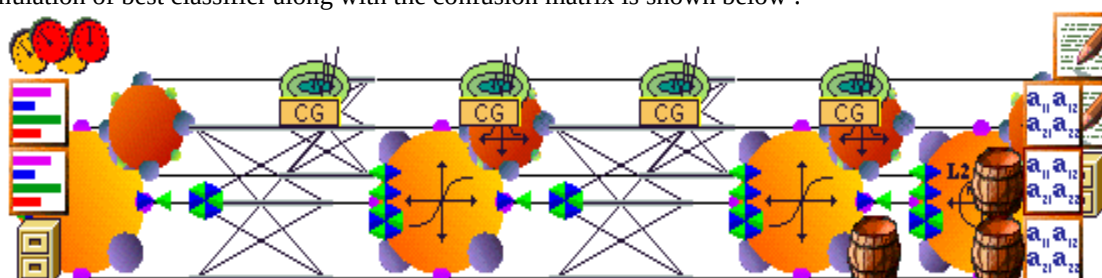


Figure.3.1 MLP neural network trained with CG learning rule

## 2) Results

| Output / Desired  | NAME(ROCK) | NAME(VOLCANO) | NAME(RIPPLE&SAND) | NAME(SHIP) | NAME(AIRPLANE) |
|-------------------|------------|---------------|-------------------|------------|----------------|
| NAME(ROCK)        | 1          | 0             | 0                 | 0          | 0              |
| NAME(VOLCANO)     | 0          | 1             | 0                 | 0          | 0              |
| NAME(RIPPLE&SAND) | 0          | 0             | 4                 | 0          | 0              |
| NAME(SHIP)        | 1          | 1             | 0                 | 4          | 1              |
| NAME(AIRPLANE)    | 0          | 0             | 0                 | 0          | 5              |

Table I. Confusion matrix on CV data set

| Output / Desired  | NAME(ROCK) | NAME(VOLCANO) | NAME(RIPPLE&SAND) | NAME(SHIP) | NAME(AIRPLANE) |
|-------------------|------------|---------------|-------------------|------------|----------------|
| NAME(ROCK)        | 4          | 0             | 0                 | 0          | 0              |
| NAME(VOLCANO)     | 0          | 6             | 0                 | 0          | 0              |
| NAME(RIPPLE&SAND) | 0          | 0             | 16                | 0          | 0              |
| NAME(SHIP)        | 0          | 0             | 0                 | 17         | 0              |
| NAME(AIRPLANE)    | 0          | 0             | 0                 | 0          | 22             |

TABLE II. Confusion matrix on Training data set

Here Table I and Table II Contend the C.V as well as Training data set.

| Performance     | NAME(ROCK) | NAME(VOLCANO) | NAME(RIPPLE&SAND) | NAME(SHIP) | NAME(AIRPLANE) |
|-----------------|------------|---------------|-------------------|------------|----------------|
| MSE             | 0.02524738 |               |                   | 0.21766232 |                |
|                 | 4          | 0.043346511   | 0.003739841       | 7          | 0.0449657      |
| NMSE            | 0.25562976 |               |                   | 1.25933203 |                |
|                 | 2          | 0.438883419   | 0.021637652       | 5          | 0.20234565     |
| MAE             | 0.10086996 |               |                   | 0.32832230 |                |
|                 | 8          | 0.1089986     | 0.049083586       | 6          | 0.121081825    |
| Min Abs Error   | 0.00089611 |               |                   | 0.00366454 |                |
|                 | 3          | 0.005036051   | 0.001568721       | 9          | 0.004110676    |
| Max Abs Error   | 0.46813036 |               |                   | 0.98200928 |                |
|                 | 2          | 0.753249943   | 0.142160875       | 0.98200928 | 0.772729902    |
| r               | 0.87087851 |               |                   | 0.52367042 |                |
|                 | 5          | 0.749310983   | 0.993055161       | 4          | 0.903704733    |
| Percent Correct | 50         | 50            | 100               | 100        | 83.33333333    |

TABLE III. Accuracy of the network on CV data set

| Performance     | NAME(ROCK)  | NAME(VOLCANO) | NAME(RIPPLE&SAND) | NAME(SHIP)  | NAME(AIRPLANE) |
|-----------------|-------------|---------------|-------------------|-------------|----------------|
| MSE             | 0.000243114 | 0.00018548    | 0.000315373       | 0.000193339 | 5.91967E-05    |
| NMSE            | 0.004209655 | 0.002213707   | 0.001699553       | 0.001001053 | 0.000264383    |
| MAE             | 0.01045412  | 0.008388089   | 0.010445962       | 0.009012494 | 0.004919254    |
| Min Abs Error   | 8.22242E-05 | 0.000207623   | 0.000157683       | 0.000187913 | 7.9992E-06     |
| Max Abs Error   | 0.048526102 | 0.05337635    | 0.05434911        | 0.046204944 | 0.034832767    |
| r               | 0.998060228 | 0.998983265   | 0.999256899       | 0.999529891 | 0.999868152    |
| Percent Correct | 100         | 100           | 100               | 100         | 100            |

TABLE IV. Accuracy of the network on training data set

Here Table III and Table IV Contain the C.V and Training result and show the 100% percent accuracy.

## IV. CONCLUSION AND FUTURE WORK

From the results obtained it concludes that the MLP Neural Network with DBD (delta by delta) and hidden layer 1 with processing element 13 gives best results of 100% in Training while in Cross Validation it gives 76.66% so overall result is 88.33%.

## V. ACKNOWLEDGMENT

We are very grateful to our HVPM College of Engineering and Technology to support and other faculty and associates of ENTIC department who are directly & indirectly helped me for these paper.

**REFERENCES**

- [1] Y. Hara, R. G. Atkins, S. H. Yueh, R. T. Shin & J. A. Kong, Application of Neural Networks to Radar Image Classification, *IEEE Trans. Geosci. Remote Sensing*, Vol. 32, 1994, pp. 100-109.
- [2] B. Sekeroglu, Classification of Sonar Images Using Back Propagation Neural Networks, IEEE IGARSS '04, Alaska 2004.
- [3] Lee, J. S., & I. Jurkevich, "Segmentation of SAR images," *IEEE Trans. Geosci. Remote Sensing*, Vol. 27, 1989, pp. 674-680.
- [4] Mingcui Zhu, Yan Song, Jia Guo, Chen Feng, Guangliang Li, Tianhong Yan, Bo He, "PCA and Kernel-based Extreme Learning Machine for Side-Scan Sonar Image Classification", IEEE 2017.
- [5] Jason Rhinelander, "Feature Extraction and Target Classification of Side-Scan Sonar Images", 978-1-5090-4240-1/16/\$31.00 ©2016 IEEE.
- [6] Marcelo Sperle, Eduardo Negri, "Automatic Classification of Sidescan Sonar Images for Mapping Marine Mineral Resources", 978-1-4673-7019-6/15/\$31.00 ©2015 IEEE.
- [7] Cristina Stolojescu-Crisan, Alexandru Isar, "The improvement of the robust exemplar-based inpainting algorithm for SONAR images", 978-1-4799-7267-8/14/\$31.00 ©2014 IEEE.
- [8] Olga Lopera, Yves Dupont, "Target classification from HR sonar image", 978-1-4799-0002-2/13/\$31.00 ©2013 IEEE.
- [9] Naveen Kumar, Qun Feng Tan, Shrikanth S. Narayanan, "OBJECT CLASSIFICATION IN SIDESCAN SONAR IMAGES WITH SPARSE REPRESENTATION TECHNIQUES", 978-1-4673-0046-9/12/\$26.00 ©2012 IEEE
- [10] BORAN SEKEROGU, "Intelligent Classification of Sonar Images", Proceedings of the 1st International Conference on Manufacturing Engineering, Quality and Production Systems
- [11] Ning Sun and Taebo Shim, "Sonar images classification of seabed physiognomy based on the information fusion methods", 978-0-7695-3119-9/08 \$25.00 © 2008 IEEE
- [12] Arnaud Martin, "Comparative study of information fusion methods for sonar images classification", 0-7803-9286-8/05 \$20.00 ©2005 IEEE
- [13] Boran Sekeroglu, "Classification of Sonar Images Using Back Propagation Neural Network", 0-7803-8742-2/04/\$20.00 (C) 2004 IEEE.