Implementation of Computational Intelligent Techniques for Diagnosis of Cancer Using Digital Signal Processor

Devesh D. Nawgaje[1], Dr. Rajendra D. Kanphade[2]

[1]Astt. Professor, EXTC Dept., Shri Sant Gajanan Maharaj College of Engineering Shegaon
Maharastra, India 444203

[2]Professor & Principal, NMIET, Pune-410507, India

ABSTRACT

***This paper presents a novel approach to implement Computational (CI) techniques like Fuzzy Logic, Adoptive Neuro-Fuzzy Inference System (ANFIS) and Neural Network for diagnosis of cancer using TMS320C6713 (Texas Instruments) DSP (Digital Signal Processor). The simulator has been developed using MATLAB and Neurosolution, while implementation has been done using code composer studio for TMS320C6713 DSP. Performance is compared by considering the metrics like accuracy of diagnosis and mean square error. The simulation and implementation result show that this CI approach can be effectively used for cancer detection to help oncologist to enhance the survival rates significantly*.**

Keywords: Computational Intelligent, Neuro-Fuzzy, Neural Network, DSP, TMS320C6713.

1. INTRODUCTION

Computational intelligent system focus on systems that use knowledge based techniques to support human decision-making, learning and action. Such systems are capable of cooperating with human user and so the quality of support given and the manner of its presentation are important issue.[1,2]

A major class of problem in medical science involves the diagnosis of disease, based upon various tests performed upon the patient. When several tests are involved, the ultimate diagnosis may be difficult to obtain, even for a medical expert. This has given rise, over the past few decades, to computerized diagnostic tools [3], intended to aid the physician in making sense out of the confusion of data.

Cancer is a group of diseases in which cells in the body grow, change, and multiply out of control. Usually, cancer is named after the body part in which it originated; thus, breast cancer refers to the erratic growth and proliferation of cells that originate in the breast tissue. A group of rapidly dividing cells may form a lump or mass of extra tissue. These masses are called tumors. Tumors can either be cancerous (malignant) or non-cancerous (benign). Malignant tumors penetrate and destroy healthy body tissues. A group of cells within a tumor may also break away and spread to other parts of the body. Cells that spread from one region of the body into another are called metastases.

The term breast cancer refers to a malignant tumor that has developed from cells in the breast. The American Cancer Society estimates that each year over 178,000 American women and 2,000 American men will be diagnosed with breast cancer. Breast cancer is the leading cause of death among women between 40 and 55 years of age and is the second overall cause of death among women (exceeded only by lung cancer). Fortunately, the mortality rate from breast cancer has decreased in recent years with an increased emphasis on early detection and more effective treatments.[4]

Leukemia is a type of cancer that affects the white blood cells. In leukemia, white blood cells become abnormal, and divide and grow in an uncontrolled way. They stay in the bone marrow and keep reproducing in an uncontrolled way. These abnormal white blood cells fill up the bone marrow and prevent it from making healthy white blood cells. This means the body is less able to fight off infections. The abnormal white blood cells also prevent bone marrow from making enough red blood cells and platelets. A lack of red blood cells leads to less oxygen being delivered to the organs and tissues of your body. This is called anemia, and it can make you feel tired and breathless. A lack of platelets can lead to problems with the blood-clotting system, and results in bleeding and bruising much more easily than usual.[5]

Soft Computing is dedicated to system solutions based on soft computing techniques. It provides rapid dissemination of important results in soft computing technologies, a fusion of research in evolutionary algorithms and genetic programming, neural science and neural net systems, fuzzy set theory and fuzzy systems, and chaos theory and chaotic systems. Soft computing encourages the integration of soft computing techniques and tools into both everyday and advanced applications. [6]

ANN and AI approaches have been used earlier in the computerized diagnostic system for cancer [5][7-14]. After experiments with ANN and ANFIS they achieved a classification accuracies ranging from 50% to 90%. The work in this paper is aimed to find not only a better accuracy and usage of ANN and ANFIS approach in diagnosis of cancer but also its implementation on TMS320C6713 DSP.

2. METHODOLOGY AND TECHNIQUES

Figure 1 shows the overall block diagram of the methodology used. Basically three following techniques are used in this work for Breast cancer and White Blood Cell Cancer.

- Fuzzy Logic for image segmentation
- Artificial Neural Network.
- Adaptive Neuro-Fuzzy Inference System

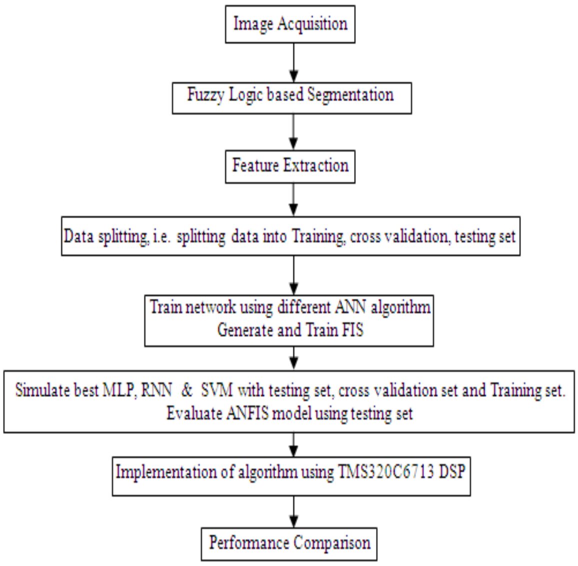

Figure 1 Block Diagram of overall methodology

2.1 Fuzzy Logic Based Segmentation

Introduced in 1965 by Zadeh [15], fuzzy set theory aims to model the vagueness and ambiguity in particular “hard” decision made in mathematics and computing. A number of fuzzy techniques have been designed for image segmentation: fuzzy clustering, fuzzy rule-based, fuzzy geometry, fuzzy thresholding and fuzzy integral based segmentation. Fuzzy rule based segmentation techniques allow expert knowledge to be incorporated into classification rules [16]. Rules in the form of linguistic variable can be used to classify image data, which eliminates numerical biases and inconsistencies. In general, rule-based techniques are less computationally expensive than fuzzy c-means based techniques.

2.2 Artificial Neural Network

ANNs are massively distributed parallel processing systems made up of highly interconnected neural computing elements that have the ability to learn and thereby acquire knowledge and make it available for use [17]. Neural networks are applicable in virtually every situation in which a relationship between the predictor variables (independents, inputs) and predicted variables (dependents, outputs) exists, even when that relationship is very complex and not easy to articulate in the usual terms of “correlations” or “differences between groups”[18,19]. In this paper three ANNs algorithms (Multi Layer Perceptron, Recurrent Neural Network and Support Vector Machine) are used.

2.3 Neuro Fuzzy System

Neuro Fuzzy (NF) computing is a popular framework for solving complex problems and is an integrated system combining the concept of FIS (Fuzzy Inference System) and ANNs. ANFIS is a fuzzy inference system implemented in the framework of adaptive networks, and hence has the advantages of both FIS and NNs.[6]

3. SIMULATION MODELS

All the four networks were evaluated on the same data set. The data set consist of 125 clinical cases. All cases are first segmented based on fuzzy logic and after feature extraction database was generated. Out of 125 clinical cases 90 cases are used for training the network, 20 cases are used for cross validation and 15 cases are used for testing. Each case has to be categorized into either of the two categories: Benign or malignant.

3.1 Fuzzy Logic Based Segmentation

The system implementation is carried out considering that their gray levels are always between 0 and 255. The fuzzy sets are created to represent each variable's intensities; these sets are associated to the linguistic variables "dark", edge and "light". The adopted membership functions for the fuzzy sets associated to the input are trapezoidal and to the output are triangular, as shown in figures 2 & 3

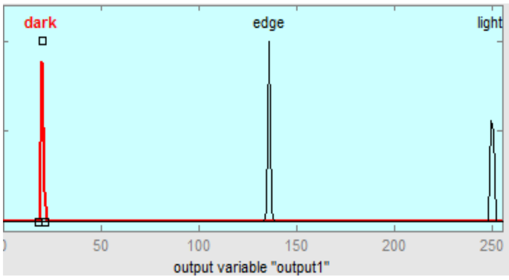

Figure 2 Membership functions of the fuzzy set associated to the input

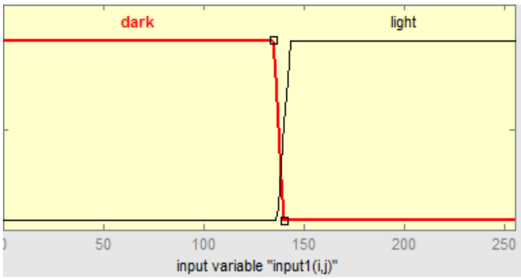

Figure 3 Membership functions of the fuzzy sets associated to the output

The functions adopted to implement the "and" and "or" operations are the minimum and maximum functions, respectively. The Mamdani method is chosen as the defuzzification procedure, which means that the fuzzy sets obtained by applying each inference rule to the input data are joined through the add function; the output of the system is then computed using weighted average method of the resulting membership function. The values of the three membership functions of the output are designed to separate the values of the blacks, whites and edges of the image.

3.2 Architecture of Network Used

3.2.1 Multilayer Perceptron

The architecture of Multilayer perceptron is shown in figure 4. MLP consist of units arranged in layers with only forward connections to units in subsequent layers. The connections have weights associated with them. Each signal traveling along the link is multiplied by the connection weight.

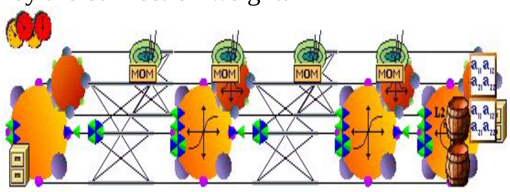

Figure 4: Architecture of multilayer perceptron

3.2.2 Recurrent neural networks

The architecture of Recurrent Network is shown in figure 5. RNN contain feedback connections. A recurrent network has, in opposition to the feedforward networks, neurons that transports a signal back through the network.

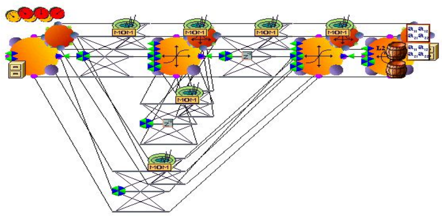

Figure 5 Architecture of Recurrent Network

3.2.3 Support Vector Machine

The architecture of SVM is shown in figure 6. SVM is primarily two-class classifier that has shown to be an attractive and more systematic approach to learning linear or non-linear decision boundaries. Given a set of points, which belong to either of two classes, SVM finds the hyper plane leaving the largest possible fraction of points of the same class on the same side, while maximizing the distance of either class from the hyper plane. Finding the optimal hyper-plane implies solving a constrained optimization problem using quadratic programming. The optimization criterion is the width of the margin between the classes.

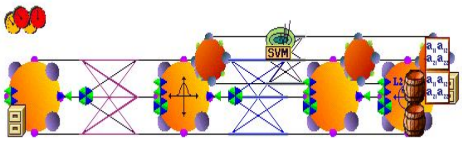

Figure 6 Architecture of SVM

3.2.4 ANFIS Structure

Figure 7 shows the structure of ANFIS. The first and fourth layers in the ANFIS are learning rules, used to tune the model adaptive layers. The first layer contains premise parameters which characterize the shape of the input membership functions. These parameters are associated with the IF part of the rule. The fourth layer also has consequent parameters, which are associated with the THEN part of the rule. Suitable learning rules are used to tune the model parameters. A hybrid learning algorithm used in ANFIS combines the gradient descent and the least squares method for an effective search for the optimal parameters. In this procedure, an ANFIS system can learn from the existing data with correct output and possibly predict a result with new input set by tuning its internal node values

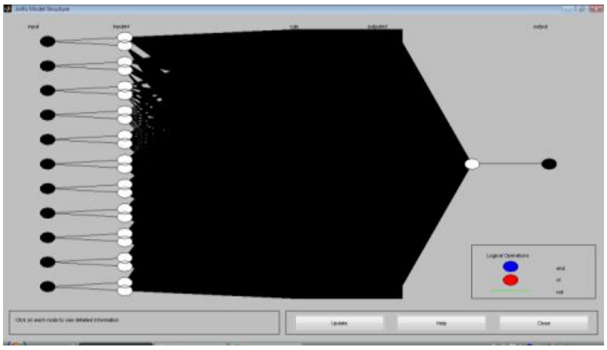

Figure 7 ANFIS structure

3.3 Implementation using TMS320C6713 DSP

The C6713 device is based on the high-performance, advanced very-long-instruction-word (VLIW) architecture developed by Texas Instruments. The TMS320C62x is a 16-bit fixed point processor and the '67x is a floating point processor, with 32-bit integer support. The C6713 DSK is a low-cost standalone development platform that enables users to evaluate and develop applications for the TI C67xx DSP family. The DSK also serves as a hardware reference design for the TMS320C6713 DSP [20].

In our work we have develop a program of fuzzy segmentation using c-code. After writing the code, the next step is to compile the code to machine language. The Build command will compile all the files that are included in this project and make an executable file for the DSP. Finally, to run the program, load the executable file (.out) that the compiler generated into the DSP and run the file loaded into DSP. The generated output of DSP is then open in image processing tool box for feature extraction. Figure 8 shows Compiler results at the bottom of the window

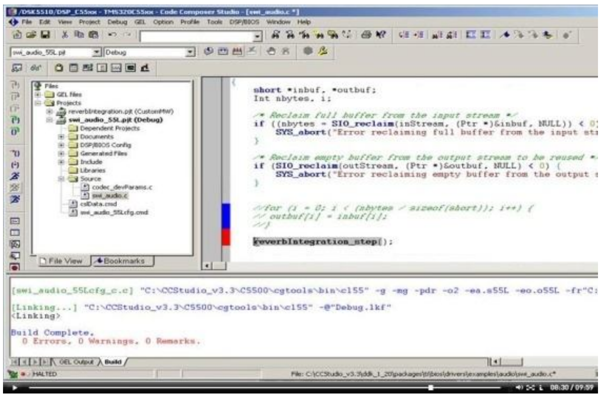

Figure 8 Compiler results

4. RESULTS AND PERFORMANCE COMPARISON

Figure 9,10,11 & 12 shows the curve for training of neural network and ANFIS with average MSE verses epoch. It can be observed from the graph that the error goes on decreasing as the no of epochs go on increasing. For MLP and RNN I/P PEs = 11, O/P PEs = 2, No. of Hidden Layers = 1, Momentum = 0.7, Function in Hidden layers and Output layers = Tanhaxon

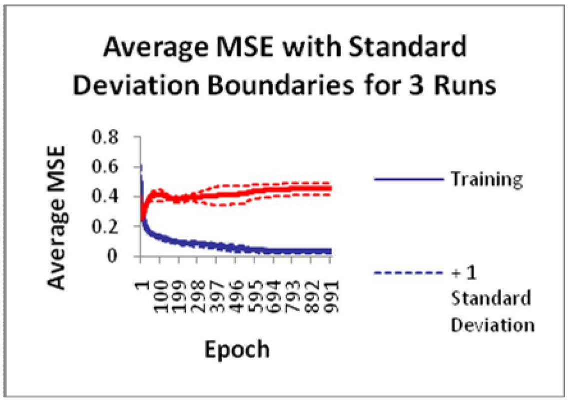

Figure 9 Training curve for MLP

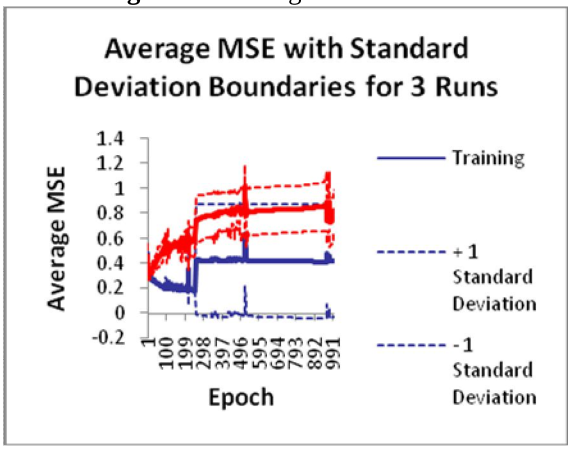

Figure 10 Training curve for RNN

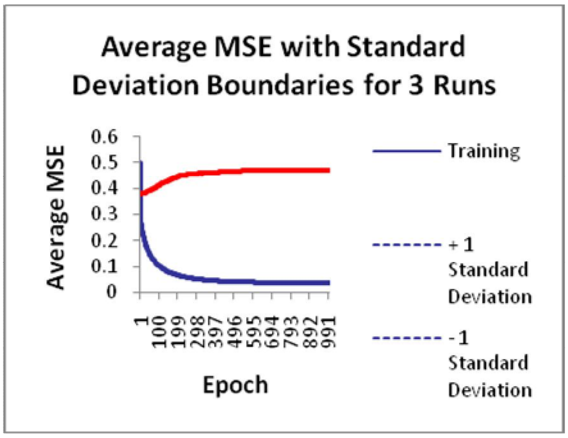

Figure 11 Training curve for SVM

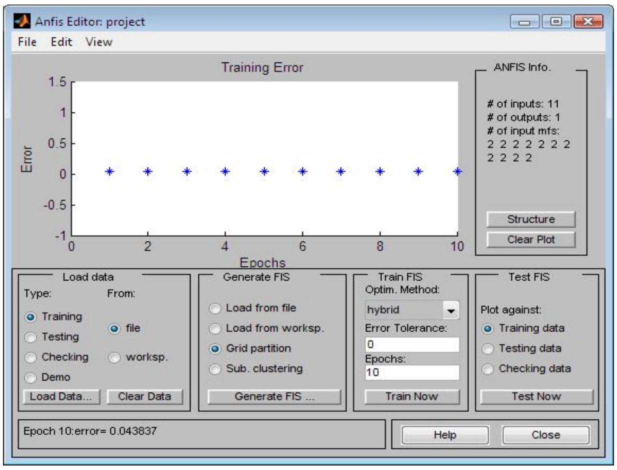

Figure 12 Training curve for ANFIS

Table 1 shows the comparison of the best results for three networks and ANFIS and depicts parameters like MSE, % of accuracy

TABLE I: COMPARISON OF THE BEST RESULTS

Network	MSE	% of Accuracy
MLP	0.0471	97.55
RNN	0.2935	90.86
SVM	0.0264	96.72
ANFIS	0.0614	95.70

5. CONCLUSION

In this paper, we have presented a system for detection and classification of micro calcification in digital mammograms & Leukemic cell. Fuzzy logic is used for segmentation of image using TMS320C6713 DSP. The algorithm for the parameters used for differentiating the malignant and benign cancer were developed and run on Matlab for the medical images obtained from the radiologist after segmentation. These data were transferred to the file and the 11 parameters were introduced to Neural-Network as the input to train them. Outputs have been shown to make to understand the accuracy of the algorithm and which helps us to detect the cancer. After the training, an unknown image was taken and tested for malignant or benign. After working on the different Neural-Network, we find multilayer perceptron has achieved a top result of accuracy 97.55%.

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