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APPLICATION OF PATTERN RECOGNITION BASED NEURAL NETWORK ALGORITHMS FOR OVARIAN CANCER DETECTION AND CLASSIFICATION

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Abstract: Ovarian cancer is a dangerous disease for women. In most cases the tumor after spreading within the pelvis and abdomen is detected, at this late detection ovarian cancer tumor is more complex to treat, so starting stage detection is important to ovarian cancers. To find the correct diagnostic sign in ovarian tumor images observed by the Ultrasound or other tests is a difficult task for gynecologists. There is a need to implement an effective computer-aided diagnostics (CAD) system for the classification of the ovarian tumor as benign and malignant, which is also inexpensive to patients because lack of cost-effective methods to early detection accrues high mortality in ovarian cancer patients. *Here* proposed a pattern recognition method for the detection and classification of ovarian cancer using various train functions of neural networks for improved accuracy and sensitivity.

***Index terms*: Ovarian cancer, computer aided diagnosis, Neural Network, Pattern recognition.**

INTRODUCTION

Ovarian cancer is an important disease to women; it does not identified until it has spread within the pelvis and stomach, after tumor spread into abdomen it is more struggling to treat. A cancer tumor can form by an abnormal cell in the ovary can starts to multiply to out of control. If not treated at this stage, the tumor can multiply in other body parts. Ovarian cancers are a group of diseases that affect the ovaries. There are different types of ovarian cancer but all are called ovarian cancer because they affect ovaries, they are different from others in terms of their origin, appearance through a microscope, test, and treatment. About 21,750 women in the US receive an ovarian cancer diagnosis in2020 and 14000 women died from it. Only 20% of ovarian cancers are detected at an early stage [1]. Nowadays the age group between 55 to 75 years that is more than 50% of ovarian cancer death will happen, and around 25% of death occur between 35 to 54 years.[U. Rajendra Acharya et. Al], with the introduction of TVUS and 3D Ultrasonography, the sensitivity specificity of ultrasonography has been improved significantly.

Mohamed Elhosony et al have developed a different approach for best subset feature were chosen from an extensive dataset and assembled by utilizing some strategies in IoMT data for better performance. His work gives better RMSE and 95% of accuracy. Lingeng lu et al proposed another framework for the detection of ovarian cancer tumor growth by measuring the correlation between lin-28B and IGF-II. H. Montazery kordy et al discovered a wavelet-based feature extraction method and filter approach for identifying the biomarker in mass spectra, they get 98% accuracy by proposed methods. A microchip- ELISA-based detection system implemented by using a charge-coupled device or a cell phone is also used for detecting ovarian cancer [shaqi, wang et al]. A CAD-based PNN classifier is used for detecting cancer by extracting features from ultrasound images and training the extracted features and finally classifying cancerous masses [U. Rajendra Acharya et al]. A special deep convolution neural network technique based on Alex net was also used to detect ovarian cancer from cytological images, from this method got 78.20% of accuracy.[Miaowu et al]. By delineating the collagen febrile morphology observed in second-harmonic generation images of women as benign or malignant [Bruce L wen et al]. The deep learning with cost-sensitive random forest classifier method was used to classify the ovarian cysts associated with color ultrasound images [Jonathan p. celli et al].

In this work, we introduced a newly technique for ovarian cancers detection and classification using various algorithms of Pattern Recognized Neural Network. Here we extract images from a popular database (FDA-NCI clinical proteomics program databank for ovarian cancer detection and classify which is normal (benign) or abnormal (malignant) by using different Neural Network techniques.

RESEARCH METHODOLOGY

2.1 Pattern Recognition neural network algorithms

The neural network for pattern recognition is a feed-forward network; it can be used to the input data for classifying the inputs according to the target classes. There are so many neural network training algorithms are available for the pattern recognition process with numerous performance factors. From that the Levenberg –Marquardt algorithm is important, it is used for second-order training speed. Its performance function is calculated by the sum of squares and Hassian matrix. The gradient of this algorithm can be measured based on Jacobian matrix and Vector of Network errors. The Bayesian regularization algorithm reduces the weights and squared errors. It changes the linear combination also so that after training, the network has high qualities.

Backpropagation is used to calculate the performance for Bayesian regularization. Newton's method is one of the best conjugate gradient methods used for speed optimization. There is a group of algorithms available; those are processed based on Newton's method but which does not require the computation of second derivatives. Rprop is another important training set, it is used to reduce the negative effects of the partial derivatives. This resilient backpropagation algorithm performance is not very sensitive to fixing the training parameters. Also, this method is faster than the normal steepest descent algorithm. The scaled conjugate gradient methods are processed based on conjugate gradient direction and do not perform line search events at every iteration. Three types of conjugate gradient methods are exits in the neural network toolbox; those are used to implement three conjugate gradient algorithms.

Another type of best algorithm is gradient descent with momentum, which allows a network to respond to local gradient also recent gradient in the error surface. Mostly used parameters of this technique are learning rate and momentum constant. Here the term momentum constant defines the momentum number. And the Batch steepest is one of the simplest methods, it uses the function trained to train the inputs. If we set the learning rate lr is high then the algorithm is unstable and set the learning rate as low then the algorithm has a long coverage time.

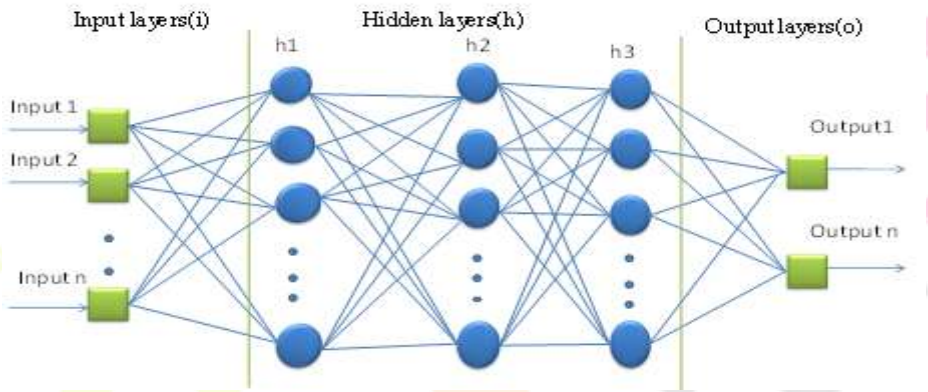

Fig 1: ***Model Neural Network Architecture***

2.2 Performance function

In our research work, the mse is used as a performance function it measures the network's performance according to the mean squared errors. The function 'perf' is used to get arguments from inputs and returns the mean square errors. The process of training of a network includes that the giving values of network biases and weights to optimize network performance as expressed by performance function. In most case 'mse' is used as performance function for feed-forward network, also it is an average squared error between network outputs (a) and target (t). The mathematical expression for the mean square error is written as

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2 \qquad (1)$$

2.3 Proposed Methodology

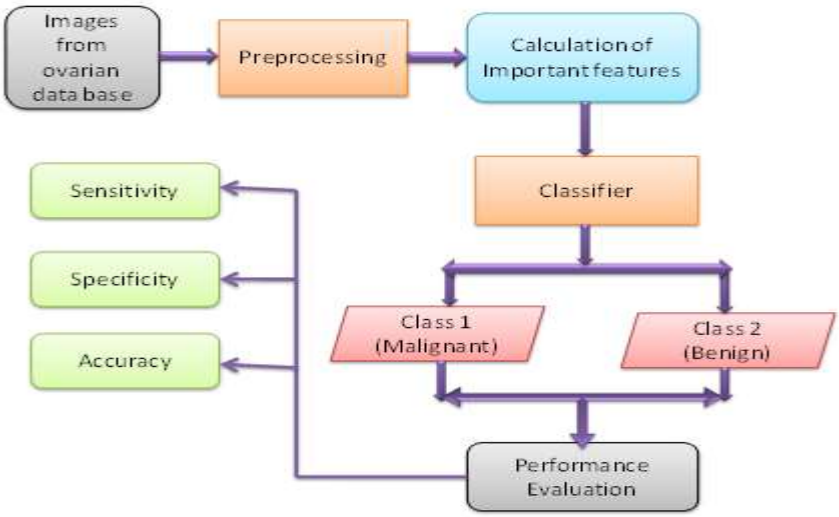

Figure 2: block diagram for ovarian cancer detection and classification

2.3.1 Ovarian cancer dataset

The database used for the detection and classification of this research work is available from the FDA-NCI clinical proteomic Program databank. This dataset aims to study how a piece of low- molecules weight information can serve as a diagnostic feature. This database is also used as a tool for the classifiers. The dataset used contains 95 controls or benign and 121 ovarian cancers or a malignant total of 216 samples. The information about the dataset and it are freely available online at the following link: HTTP:// home.ccr.cancer.gov/ncifdaproteomic/pptterns.asp.

2.3.2 Preprocessing and Feature Extraction

Preprocessing is reduced any noise in the image to detect the tumor. Database image is input to this unit. In this section noise of the image is reduced and enhanced image using various filtering methods. Feature extraction is a technique used to change the visually extractable and non-extractable features into mathematical descriptors. Any pathological or traumatic discontinuity of tissue or loss of function of a part of the body is named a lesion; this module contains statistical features that are classified as Transform Domain features.

2.3.3 Classifier

In the case of ovarian cancer classification, we used ANN architecture consisting of 20 hidden layers with 100 nodes and an output layer with two nodes, whose value inform as cancer or control. Here the function cross-entropy is used for feature extraction to provide good performance. All training algorithms are working for ANN training for selecting one of the best algorithms out of all, that algorithm gives better performances features than others for ovarian cancer database. Best results were acquired using scaled conjugate gradient and Conjugate gradient with Powell-Beale algorithms**.**

2.4 Tool used for signal processing

In this research work**,** MATLAB is employed as a tool for signal processing. It is a performance-oriented high-level programming numerical computing environment that incorporates visualization, mathematical computation, and programming in a friendly way. It has many .inbuilt commands and functions for performing mathematical calculations and is also used for displaying the graphical representation. It has tools for image and signal processing that supports to design and analysis of images by linear filtering algorithms. Most software engineers and scientists have used this software to target the required results by selecting the proper tools and features.

III. RESULT AND DISCUSSION

3.1 Evaluation matrixes

The findings of the suggested ovarian cancer detection and classification technique are discussed in this section. We utilized Matlab version 2014a to configure the proposed approach. This technique was tested on a Windows computer with a 1.6 GHz Intel Core i5 processor and 4 GB RAM. The proposed technique has been verified on a database for ovarian cancer that is freely got on the source of the internet. Three evaluation matrixes are calculated from the confusion matrix by using the following expressions

3.1.1 Sensitivity

The sensitivity of tumor detection is determined by taking the ratio of the number of true positives to the sum of true positives (TP) and true negatives (TN). This relation can be expressed as:

$$ST = \frac{TP}{TP+TN} \tag{2}$$

3.1.2 Specificity

The specificity of the cancer lesion detection can be evaluated by the factors number of true negatives (TN) and the combined number of true negative (TN) and false positive (FP). This specificity can be expressed as:

$$SP = \frac{TN}{TN+FP} \tag{3}$$

3.1.3 Accuracy

The accuracy of the breast cancer lesion identification can be calculated by taking the ratio of the true values present. This accuracy can be expressed by the following equation.

$$A = \frac{TP+TN}{TP+FP+FN+TN} \tag{4}$$

3.2 Observations after training and testing database

The following section described about the performance analysis of various pattern recognition neural network training algorithms and different types ofccharacteristics plots like training performance plot, training state plot, ROC plot and confusion matrix plot.

3.2.1 Performance study for various training algorithms

Table 1-Results of ovarian cancer detection and classification after testing for various algorithms

S.No	Training algorithm	Gradient	Performance by mean square error(mse)				Accuracy in percentage
			Train perf	**Val. Perf**	**Test perf**	**Total perf**	
1	Levenberg-Marquardt	0.0116	0.13	0.15	0.13	0.131	97.91%
2	BFGS quasi-Newton	0.0742	0.36	0.33	0.40	0.359	9 5.83%
3	Resilient backpropagation	0.0261	0.40	0.36	0.38	0.382	91.66%
4	Scaled conjugate gradient	0.0055	0.34	0.34	0.41	0.344	98.14%
5	Conjugate gradient with Powell-Beale restarts	0.0180	0.35	0.34	0.40	0.343	98.14%
6	Conjugate gradient with Fletcher-Reeves	0.0690	0.38	0.35	0.37	0.376	95.37%
7	Conjugate gradient with Polak-Ribiére	0.00044	0.34	0.35	0.45	0.341	96.75%
8	Gradient descent	0.0551	0.40	0.35	0.36	0.43	93.05%
9	Gradient descent with momentum	0.0553	0.40	0.35	0.36	0.43	93.05%

3.2.2 Outputs observed by neural network training process

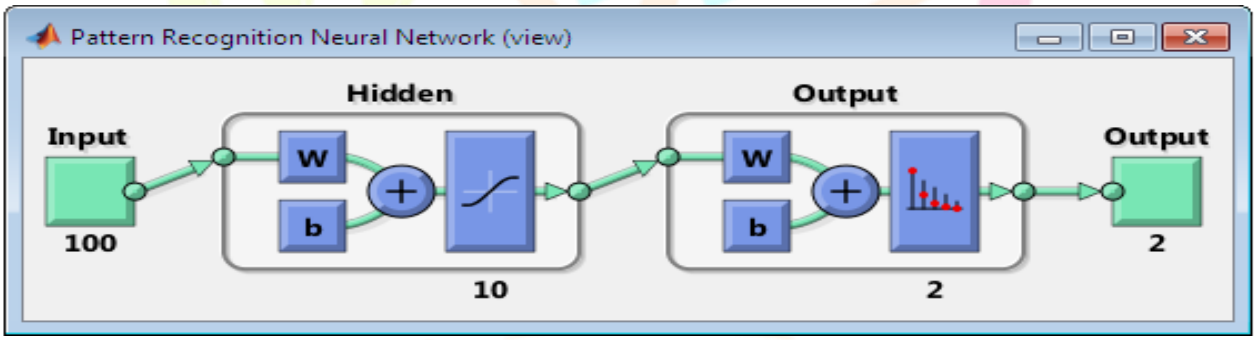

Fig a: Pattern Recognition Neural Network Architecture for Ovarian Cancer detection

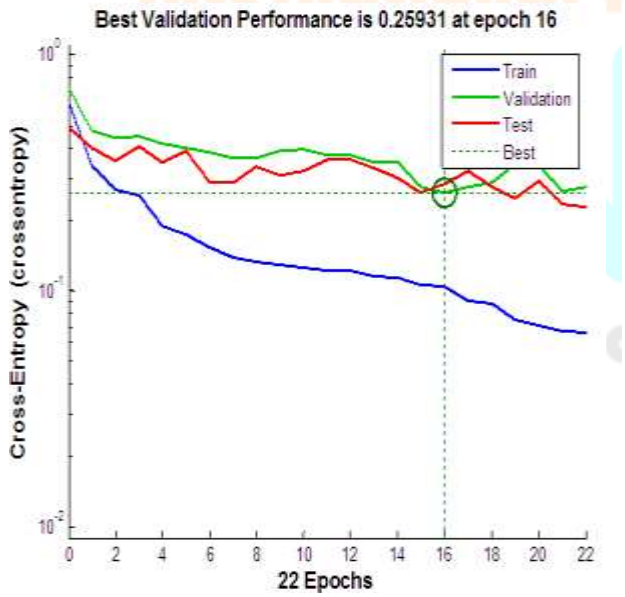

Fig b: Training performance plot

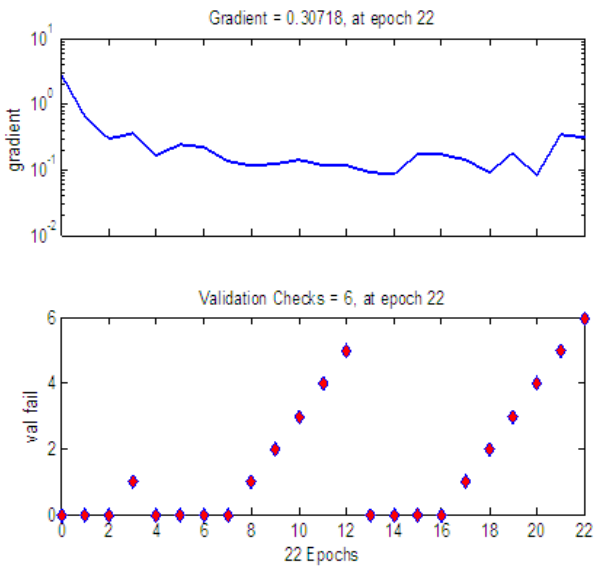

fig c: Training state plot

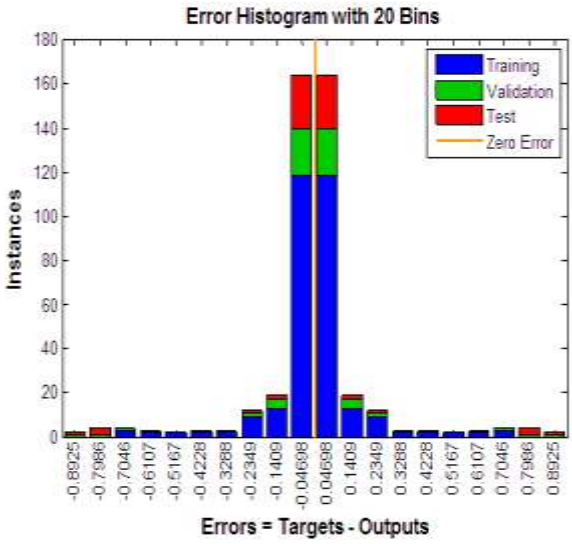

Fig d: Error histogram with 20 bins

Fig e: All Confusion matrix plat

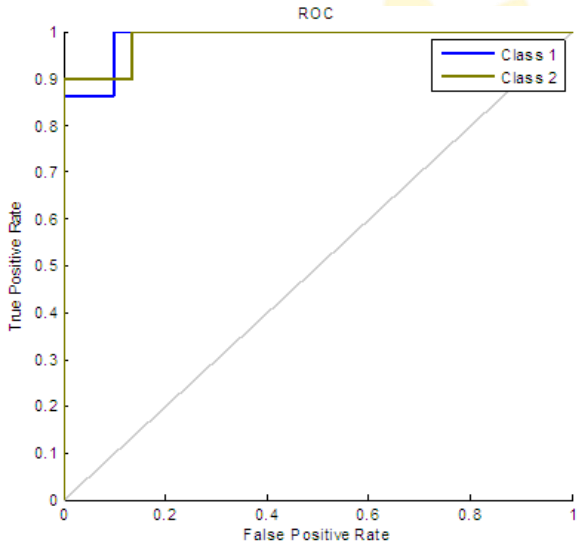

Fig f: ROC plot

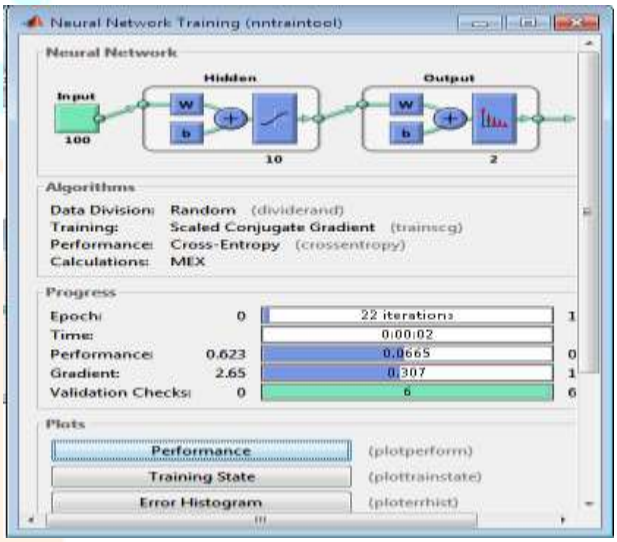

Fig g: Neural network training

CONCLUSION

Ovarian Cancer is the most dangerous disease. A patient life can be saved by detecting cancers at an early stage. From my literature review, many techniques exist with some limitations. In our proposed algorithm, the pattern recognition neural network successfully detected the cancerous cells from ovarian cancer images and classified them by the proposed algorithm with 98% accuracy. It gives better accuracy than compared to other algorithms. The cancerous cells are found at the early stages then the life of the patient can be saved, which improves the survival ratio.

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