A Computational Intelligence Based Classification of Endoscopic Tympanic Membrane Images

Roshani Deepak Pendhari[1], Dr.V.L Agrawal[2]
[1]*Student, Electronic and Telecommunication of HVPM'S, College of Engineering and Technology, India*
[2]*Professor, Electronic and Telecommunication of HVPM'S, College of Engineering and Technology, India*

***Abstract*— In this paper classification Endoscopic Tympanic Membrane Images , which uses the WHT transform over the Tympanic Membrane images as feature detector and a constructive one hidden layer Multilayer perceptron neural network as classification Tympanic Membrane Images classifier technique is applied to a database consisting of images of 115 having endoscopic Tympanic Membrane Images. It is demonstrated that the best recognition rates are 97.29%. Finally, optimal algorithm has been developed on the basis of the best classifier performance. The Genetic algorithm will provide an effective alternative method of Classification endoscopic Tympanic Membrane using Neural Network Approach.**

***Index Terms*—Neural network, Microsoft excel, MatLab, Endoscopic Tympanic Membrane Images.**

I. INTRODUCTION

The tympanic membrane (TM) plays an important role in the physiology of hearing as well as in the pathophysiology of inflammatory middle ear diseases. The TM perforation is a common sequel of long-standing and recurrent inflammatory middle eardiseases. The TM has a tremendous capability to heal after injury while most of the TM perforations heal spontaneously. Despite this high healing capability, the closing of chronic TM perforations is still a crucial issue for otolarygologists in terms of finding a simple method to heal it. The chronic TM perforations significantly impair the quality of life for millions of patients. The anatomy and the hearing physiology of the TMs have been well documented during the past several decades. Sufficient knowledge about the mechano-acoustic behaviour of myringotomized and healed TM is still lacking. In the search for the simple treatment of chronic TM perforations it is important to evaluate the mechanical along with the structural outcome.

The ear is the organ of the human body that functions as the sense of hearing and the organ that maintains the balance of the human body. In Ear tympanic membrane Are present tympanic membrane, also called eardrum, thin layer of tissue in the human ear that receives sound vibrations from the outer air and transmits them to the auditory ossicles, which are tiny bones in the tympanic (middle-ear) cavity. It additionally fills in as the horizontal mass of the tympanic depression, isolating it from the outside hear-able waterway. The layer lies across the finish of the outer channel and seems to be a leveled cone with its tip (apex) pointed internal. The edges are attached to a ring of bone, the tympanic annulus. tympanic membrane, also called eardrum, thin layer of tissue in the human ear that gets sound vibrations from the external air and communicates them to the hear-able ossicles, which are minuscule bones in the tympanic (center ear) hole. It additionally fills in as the parallel mass of the tympanic hole, separating it from the external auditory canal. The membrane lies across the end of the external canal and looks like a flattened cone with its tip (apex) pointed inward. The edges are attached to a ring of bone, the tympanic annulus. tympanic membrane, also called eardrum, thin layer of tissue in the human ear that receives sound vibrations from the outer air and transmits them to the auditory ossicles, which are tiny bones in the tympanic (middle-ear) cavity. It also serves as the lateral wall of the tympanic cavity, separating it from the external auditory canal. The membrane lies across the end of the external canal and looks like a flattened cone with its tip (apex) pointed inward. The edges are attached to a ring of bone, the tympanic annulus.

Computer-aided diagnosis of human diseases using various medical images has recently become a very active research topic [1, 2]. Such exploration can help human specialists in diminishing the gamble of misdiagnose and lessening work. Furthermore, it empowers the exchange of excellent clinical assets to less created areas. This work is concerned with a particular task of medical image based diagnosis, i.e., the diagnosis of otitis media (OM) using endoscopic tympanic membrane (ETM) images.OM is a world-wide high-rate disease for children, which may cause severe hearing damage or even life-threatening consequences in case of misdiagnosis or missed diagnosis. Clinically, ETM images for OM diagnosis are typically required to be categorized into four classes, including normal (NORM), secretory otitis media (SOM), active chronic suppurative otitis media (ACSOM), and static chronic suppurative otitis

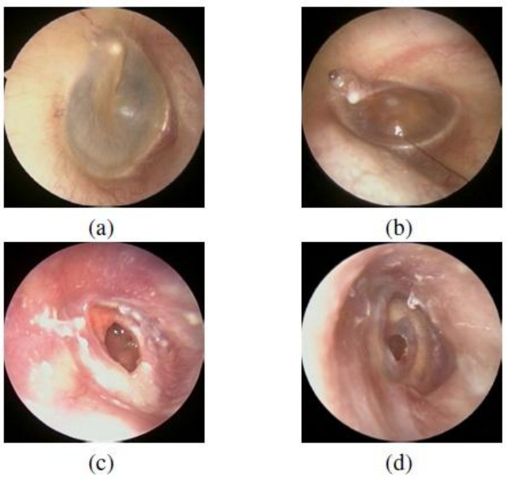

Figure1. Some exemplary endoscopic tympanic membrane images of various classes (a) NORM, (b) SOM, (c) ACSOM, and (d) SCSOM.

Media (SCSOM). Some exemplary images are presented in Fig. 1. Usually captured by a hand-held optical endoscope from arbitrary perspectives, these images may contain large variations, which makes accurate classification very challenging.

Based on WHO data there are 466 million people in the world who have hearing loss. This is more than 5% of the world's population; 34 million of these are children. If no action is taken, by 2030 there will be nearly 630 million people with hearing loss. In 2050, the number could increase to more than 900 million [2]. The data shows that hearing loss is still a public health problem. The priority of hearing prevention programs in Indonesia is focused on preventable diseases, one of which is Otitis Media. This ear disease is usually treated by general practitioners and otolaryngologists. Otolaryngology is a branch of medicine that specializes in the diagnosis and treatment of ear, nose, throat and head and neck diseases. In Indonesia, this branch of medicine is popularly known as the Ear Nose Throat Surgery, Head and Neck Surgery, ENT-KL. [3] the video camera and light source will then display the image on the screen. But the examination is still done with the naked eye, it is considered less effective because it takes time, energy and very high concentration. In addition, the results of different diagnoses depend on the expertise and experience of medical personnel to enable human error. Therefore, an automatic system is needed that can help the doctor in providing a diagnosis and analysis to determine the state of the eardrum either the normal ear or eardrum with otitis media which is done on the endoscope image.

III. ALGORITHM

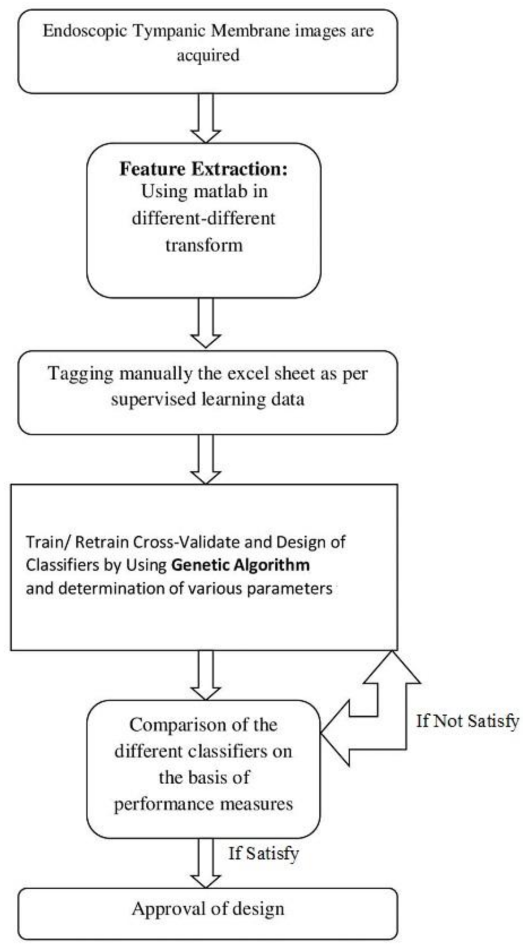

Figure 2: Flow chart

3.1Genatic Algorithm:

Trains the active NeuroSolutions breadboard while genetically optimizing the networks choice of inputs, step sizes, momentum values, and the number of processing elements in the hidden layer(s) (Note: Other parameters can also be optimized by setting them up manually within NeuroSolutions). The goal of the optimization is to find the parameter settings that result in the minimum error. If cross validation is used, the goal will be to minimize the cross validation error. Otherwise, the goal will be to minimize the training error. The best weights and parameter settings will automatically be saved during training and can be loaded into the NeuroSolutions breadboard by clicking the Load Best Weights menu item. However, this is not normally necessary since the best weights and parameters will automatically be loaded during testing (if the Load Best option is selected – the default) or during the application of the Production dataset.

To perform hereditary preparation, initial an underlying populace of organizations is haphazardly made with each having an alternate arrangement of boundaries. Every one of these organizations is then prepared and assessed (to decide its wellness) in view of the base blunder it accomplished. The attributes of the great organizations are then joined and changed to make another populace of organizations. Once more, the organizations in this populace are assessed and the qualities of the best organizations are given to the up and coming age of organizations. This interaction is rehashed until the Maximum Generations or Maximum Evolution Time is reached or the client stops the development. After training, a report is automatically generated summarizing the results. The generated report contains the following information:

1. Plot of the best fitness achieved during each generation of the optimization. The best fitness is the overall minimum MSE (cross validation MSE if cross validation was used or the training MSE otherwise) among all of the networks within the corresponding generation.
2. Plot of the average fitness achieved during each generation of the optimization. The average fitness is the average of the minimum MSE (cross validation MSE if cross validation was used or the training MSE otherwise) taken across all of the networks within the corresponding generation.
3. Table summarizing the best fitness and the average fitness plots. For each of these plots, the minimum MSE (across all generations), the generation of this minimum, and the final MSE are displayed.

In this paper to study classification of Endoscopic Tympanic Membrane images Using Neural Network Approaches. Data acquisition for the proposed classifier designed for the classification of Endoscopic Tympanic Membrane images using neural network approach. Image data will be collected from the different- different ENT hospital. The most important un correlated features as well as coefficient from the images will be extracted .In order to extract features, statistical techniques, image processing techniques, transformed domain will be used.

IV. NEURAL NETWORKS

Following Neural Networks are tested:

4.1Multilayer perceptron (MLP)

The most well-known brain network model is the multi-facet perceptron (MLP). This sort of brain network is known as a regulated organization since it requires an ideal result to learn. The objective of this sort of organization is to make a model that accurately maps the contribution to the result utilizing verifiable information so the model can then be utilized to deliver the result when the ideal result is obscure. A graphical representation of an MLP is shown below:

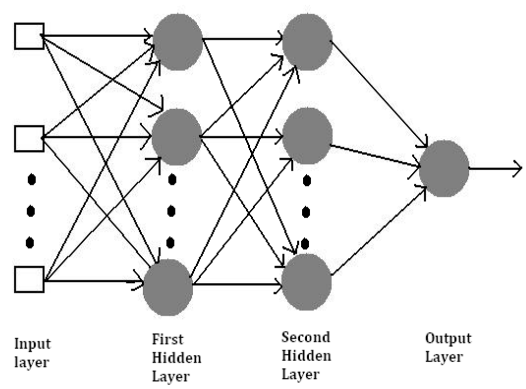

Figure3. THE STRUCTURE OF NEURAL NETWORK MODEL MLP

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".

4.2Delta bar Delta (DBD):

Delta-Bar-Delta algorithm is an adaptive step-size procedure for searching a performance surface. The step size and momentum are adapted according to the previous values of the error at the PE. If the current and past weight updates are both of the same sign, the learning rate is increased linearly. The reasoning is that if the weight is being moved in the same direction to decrease the error, then it will get there faster with a larger step size. If the updates have different signs, this is an indication that the weight has been moved too far. When this happens, the learning rate decreases geometrically.

$$\Delta\eta_i(\mathrm{n}) = \begin{cases} K & s_i(n-1)\Delta w_i(n) > 0 \\ -\beta\eta_i(\mathrm{n}) & s_i(n-1)\Delta w_i(n) < 0 \\ 0 & Otherwise \end{cases} \quad \ldots\ldots\ldots\ldots\ldots (21)$$

Where: $S_i(n) = (1-\lambda)\nabla w_i(n-1) + \lambda S_i(n-1)$

K= Additive constant
B= Multiplication constant
λ= Smoothing factor
Weight update Equation:

$$\nabla w_i(n-1) = \eta_i \nabla w_i + \rho\Delta w_i(n) \quad \ldots. (22)$$

V. RESULT SIMULATION

The Best Neural network with maximum accuracy is shown below:

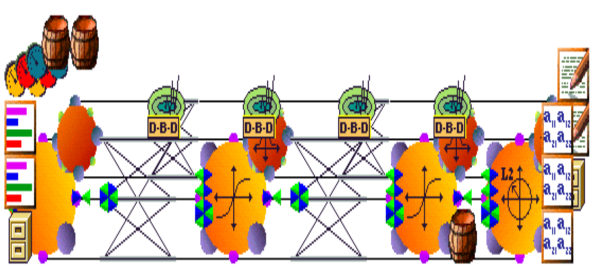

Figure.4 The Best Neural network with maximum accuracy

Test on Cross validation (CV):

Output / Desired	SCSOM	ACSOM	SOM	NORM
SCSOM	3	0	0	0
ACSOM	0	2	0	0
SOM	0	0	2	0
NORM	0	0	0	5

Table 1: Test on Cross validation (CV)

Performance	NAME(SCSOM)	NAME(ACSOM)	NAME(SOM)	NAME(NORM)
MSE	0.037505222	0.027601048	0.006461579	0.011563405
NMSE	0.200027853	0.198727548	0.046523366	0.047575152
MAE	0.165181722	0.117860851	0.060298637	0.08666274
Min Abs Error	0.052880638	0.010584242	0.007315679	0.02059457
Max Abs Error	0.286760523	0.365003155	0.17481329	0.226193266
r	0.90807414	0.899389954	0.996392099	0.998327185
Percent Correct	100	100	100	100

Table 2: Performance Measures for cross validation

Test on Training:

Output / Desired	SCSOM	ACSOM	SOM	NORM
SCSOM	25	2	0	0
ACSOM	0	15	0	2
SOM	0	1	17	1
NORM	0	0	0	40

Table 3: Test on Training

Performance	NAME(SCSOM)	NAME(ACSOM)	NAME(SOM)	NAME(NORM)
MSE	0.019442561	0.038632258	0.018543991	0.025825741
NMSE	0.1057775	0.26787557	0.134564434	0.106195846
MAE	0.076383773	0.088245872	0.07620709	0.087572514
Min Abs Error	0.000105036	0.006273787	0.002958365	0.002193324
Max Abs Error	0.667280326	0.983685217	0.772952388	0.807873047
r	0.947184367	0.864456388	0.933138712	0.947748666
Percent Correct	100	83.33333333	100	93.02325581

Table 4: Performance Measures for training

VI. CONCLUSION

From the results obtained in WHT domain it concludes that the MLP Neural Network with DBD (Delta by Delta) and hidden layer 1 with processing element 8 gives best results of 97.29% Accuracy.

ACKNOWLEDGMENT

We are very grateful to our H.V.P.M college of engineering and technology Amravati to support and other faculty and associates of ENTC department who are directly & indirectly helped me for these paper.

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