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A REVIEW: COMPUTATIONAL INTELLIGENCE BASED CLASSIFICATION OF ENDOSCOPIC TYMPANIC MEMBRANE IMAGES

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***Abstract*— Use of computational strategies in the field of medication has been an area of extraordinary exploration as of late. This paper proposes an efficient technique for automatic detection of the tympanic membrane / eardrum in an endoscope image. All this time, the examination of the eardrum is done manually by a doctor to possibility for human errors. Then we need a system to help doctors diagnose the eardrum. Hence automatic detection of these diseases through computational techniques would be a great remedy. In this proposed work, order and discovery of exudates in shading tympanic membrane images utilizing computerized procedure have been proposed.**

***Index Terms*—Neural network, Microsoft excel, MatLab, normal and diabetic retina scan images.**

I. INTRODUCTION

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

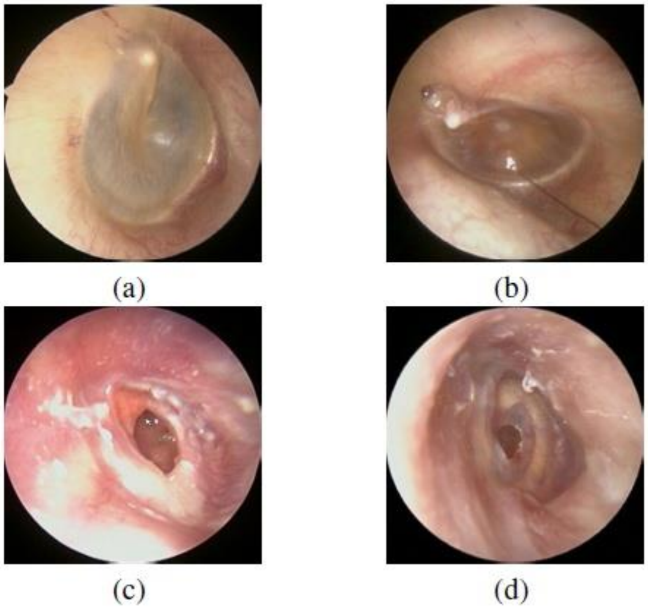


Fig. 1. Some exemplary endoscopic tympanic membrane images of various classes (a) NORM, (b) SOM, (c) ACSOM, and (d) SCSOM.

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.

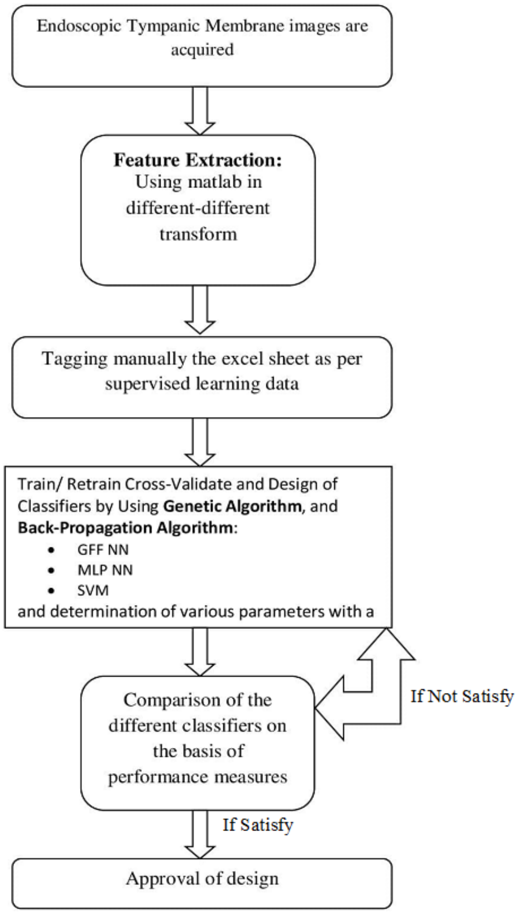
II LITERATURE REVIEW

Although biomedical image processing has increased in the last few decades, there are only a few studies working on image processing from otitis media. Satish Bhairannawar end friends [5] Using color image enhancement and contrast limited adaptive histogram equalization methods that are effective for enhancing colors and lighting in images, image enhancement is a technique to improve the perception of information in an image to provide better visualization. The author adopts this method because it is felt to have the same goal of improving image quality by increasing contrast without changing the color quality of the image used.

Anupama Kuruvilla and friends [6] Create an algorithm to classify diagnostic categories of otitis media (middle ear inflammation), acute otitis media, otitis media effusion and chronic otitis media. Based on visual cues that exist in otoscopy images so that the characteristics for each otitis media category are obtained. The author uses the feature references in this paper to determine the categories for each eardrum. Here are some related studies, Constantin Vertan [7] Using a real time system for analyzing images on video-otoscopy by using feature extraction in the form of assessing the color distribution displayed in the form of a graph to choose a decision from 0 to 3 for the total number of false alarm ratios and miss detection ratios. In this study presents special color characteristics for the tympanic membrane / eardrum for normal conditions with otitis media contour. By measuring the chromatic coordinates of the color space modeling the color distribution using the Gaussian method with 2 modes to make the diagnosis support function simple.

Chuen-Kai Shie [8] Using the method of segmentation in the otoscopy image with the active contour model method, using the color and texture feature extraction method which has an accuracy rate of 88.06% for system classification, with 3 kinds of diagnosis of the eardrum. This system still uses the old method, the active contour model which currently cannot be used in the latest OpenCV, so it needs to be developed and the accuracy results also need to be improved, adopting the method of taking features for classification because it has a strong influence on the system.

III. PROPOSED METHODOLOGY



Computational Intelligence techniques include the following will established techniques.

i) Statistics
ii) Image processing
iii) Learning Machines such as neural network .
iv) Transformed domain techniques such as FFT, DCT,WHT etc.

For choice of suitable classifier following configuration will be investigated.

i) Multilayer perceptron Neural network.
ii) Support vector machine.
iii) Generalized Feed Forward Neural Network

For each of the architecture, following parameters are verified until the best performance is obtained.

i) Train-CV-Test data
ii) Retraining at least five times with different random initialization of the connection weights in every training run.
iii) Possibility different learning algorithms such as Genetic Algorithm, Standard Back-Propagation algorithm, Conjugate gradient, Quick propagation, Delta Bar Delta, Momentum Learning Rules.
iv) Number of hidden layers
v) Number of processing elements of neurons in each hidden layer.

After regions training & retraining of the classifier, it is cross validated & tested on the basis of the following performance matrix.

i) Mean Square Error
ii) Normalized Mean Square Error
iii) Classification accuracy

In order to carry out the proposed research work, Platforms/Software's such as Matlab, Neuro solutions, Microsoft Excel will be used.

RESEARCH OBJECTIVES:

i)To maintain the correctness & accuracy in the Classification Of Endoscopic Tympanic Membrane Images even though the input images are contaminated by known or unknown noise.

ii)To increase the classification accuracy for Classification Of Endoscopic Tympanic Membrane Images.

IMPLICATIONS:

Use of the proposed optimal classifier based on Computational Intelligence techniques will be result in more accurate and reliable Classification Of Endoscopic Tympanic Membrane Images.Using our system, ENT Specialist can diagnose Of Endoscopic Tympanic Membrane Images with enough confidence. Moreover, our system can also be used by the experts in order to confirm their diagnostic decision.

IV. CONCLUSION

This paper demonstrated how to using artificial neural networks(ANN)could be used to build accurate Classification of endoscopic tympanic membrane images and i am also try to achieved result more accurate and reliable.

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