EAR DISEASE DETECTION BY OTOSCOPIC IMAGES USING MATLAB

Mrs.P. Subhasundari [1], M. Balamurugan [2], N. Gokul [3], J. Akshyavarshini [4]

[1,2,3,4]Department of Electronics and Communication Engineering,
Muthayammal Engineering College, Rasipuram

E-mail : [1]subhasundhariece@gmail.com ,[2] bala.pro33@gmail.com ,[3]gokuln3929@gmail.com, [4] akshyavarshini0702@gmail.com

Abstract

The diagnosis and classification of ear diseases play a pivotal role in the early detection and effective treatment of various auditory disorders. In this project, we propose a machine learning-based model and ADAM optimization algorithm approach for the automated detection and classification of ear diseases using otoscopic images. The focus of our investigation lies in the classification of ear diseases based on tympanic membrane conditions, encompassing a range of conditions with normal ear and acute otitis media, chronic otitis, ear ventilation issues, earwax accumulation, otitis externa, pseudo membrane presence, and tympanosclerosis.

Keywords: machine learning, ear diseases, otoscopic images, tymphanic membrane.

1. INTRODUCTION

Ear diseases pose significant health challenges worldwide, impacting millions of individuals across all age groups. Timely and accurate diagnosis of these conditions is crucial for effective treatment and management. In recent years, deep learning techniques, particularly convolutional neural networks (CNNs), have emerged as powerful tools for medical image analysis, offering the potential to automate disease detection processes with high accuracy and efficiency. In this study, we leverage a customized CNN architecture and the ADAM optimization algorithm to develop a deep learning model for the automated detection of ear diseases from otoscopic images. By harnessing the capabilities of deep learning and image processing techniques, we aim to address the challenges associated with manual diagnosis, such as subjectivity and variability in interpretation.

1.1 Contributions and Major Issues Addressed

The primary contribution of this work lies in the development of a robust and accurate deep learning model tailored specifically for ear disease detection. By customizing the CNN architecture and optimizing model parameters using the ADAM optimizer, we strive to achieve superior performance in disease classification tasks. Additionally, the incorporation of data augmentation techniques enhances the model's ability to generalize across diverse datasets, thereby improving its reliability in real-world applications

2. PROPOSED METHOD

The proposed system introduces novel data augmentation techniques, enhancing the diversity of the training dataset. This improves the model's ability to handle variations in otoscopic images, making it more resilient to challenges posed by limited labelled medical images. Performance metrics and evaluation processes are refined to provide a more comprehensive assessment of the model's effectiveness. New metrics may be introduced, ensuring a thorough understanding of the model's strengths and areas for improvement.

2.1 Phases of Proposed work

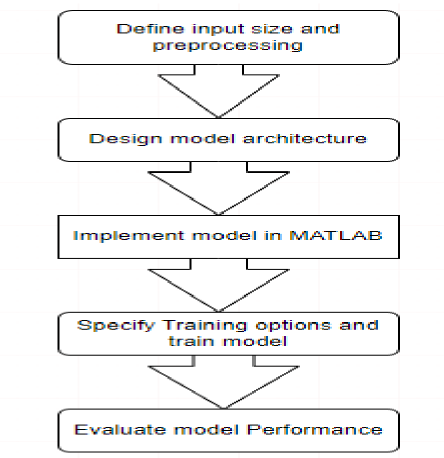

Figure 1: Flowchart of phases of proposed work

2.2 REVIEW OF LITERATURE

2.2.1 Diagnosis of Ear conditions using Deep Learning approach. Only two diseases are classified

Akriti Singh et al. describes a Diagnosis of Ear conditions using Deep Learning approach. Only two diseases are classified. Convolutional Neural Networks (CNNs) represent a specialized class of deep neural networks designed for image processing and pattern recognition.

2.2.2 Assistive role of a machine learning network in diagnosis of middle ear disease

Hayoung Byun et al. describes an assistive role of a machine learning network in diagnosis of middle ear disease. The ResNet 18 architecture is used in this machine learning model. One aim of the present study was to evaluate the assistive role of a machine learning network in classifying tympanic membrane images.

2.2.3 Deep learning algorithm for identification for ear diseases

K. Manju et al. describes the deep learning algorithm for identification for ear diseases. The VGG – 19 architecture is used for the deep learning architecture to train the machine learning model. Current studies are unparalleled regarding disease diversity and diagnostic precision

2.2.4 Automatic detection of tympanic membrane and middle ear infection from otoendoscopic images via convolutional neural networks

Mohammad Azam Khan et al. describes the Automatic detection of tympanic membrane and middle ear infection from oto-endoscopic images via convolutional neural networks. In this project only three types of categories are classified with small number of datasets.

2.2.5 Automated diagnosis of ear disease using ensemble deep learning

Dongchul Cha et al. describes the Automated diagnosis of ear disease using ensemble deep learning. Here the method ensemble learning is used to train the machine learning model. But for the ensemble learning the learning rate is very maximum with the vast fine tuning process.

3. EASE OF USE

3.1Disease Classification

The classification of ear diseases is a critical component of our machine learning-based system. Each disease is discerned through the analysis of distinct patterns present in otoscopic images, primarily focusing on the conditions of the tympanic membrane. The diseases included in the classification system are as follows:

- Normal Ear
- Acute Otitis Media
- Chronic Otitis
- Ear Ventilation
- Earwax Accumulation
- Otitis Externa
- Pseudo Membrane
- Tympanosclerosis

3.2 METHODOLOGY

3.2.1. Dataset

The dataset used in this project plays a pivotal role in training a robust and accurate machine learning model. It consists of otoscopic images collected from diverse sources, covering a spectrum of ear diseases and conditions.

The dataset is divided into three subsets:

(i) Training Set (70%)

(ii) Validation Set (20%)

(iii) Test Set (10%)

Table 1 : Count of Datasets used

S. No	Name of the Disease	No of datasets used
1.	Normal Ear	400
2.	Acute Otitis Media	120
3.	Chronic	63
4.	Ear Ventilation	30
5.	Earwax	141
6.	Otitis Externa	41
7.	Pseudo Membrane	20
8.	Tympanosclerosis	30

3.3 Customized Architecture Model :

3.3.1 Input Layer 224*224*3:

This layer defines the input size of the images. It expects images of size 224x224 pixels with 3 color channels (RGB). The input layer serves as the initial entry point for your images within your neural network architecture.

3.3.2 (3*3) Convolutional Layer 1, 32 :

Convolutional layer with a 3x3 filter size and 32 filters. 'Padding' is set to 'same' to maintain the spatial dimensions of the input. Convolutional layer plays a crucial role in feature extraction. It applies a series of filters to the input data (images of the ear canal in your case) to detect various patterns and features such as edges, textures, and shapes.

3.3.3 Batch Normalization ReLu:

Batch normalization helps stabilize and accelerate the training process by normalizing the inputs to the layer. Batch normalization layer plays a crucial role in normalizing the inputs of each layer in a mini-batch of data.

3.3.4 (2*2) Max Pooling layer 1:

Max pooling reduces spatial dimensions by selecting the maximum value in each region, aiding in feature extraction and dimensionality reduction. In your ear disease detection project using MATLAB, the

2x2 max pooling layer serves to downsample the feature maps obtained from the previous convolutional layers.

3.3.5 (3*3) Convolutional Layer 2,64 :

3*3 Convolutional layer indicates that the layer performs convolutions using 3x3 filters. Convolution is a fundamental operation in CNNs where a filter (also known as a kernel) slides over the input data, performing element-wise multiplication with the data and summing the results to produce a feature map.

2*64 This indicates that the layer performs convolutions using 3x3 filters. Convolution is a fundamental operation in CNNs where a filter (also known as a kernel) slides over the input data, performing element-wise multiplication with the data and summing the results to produce a feature map.

3.3.6 Batch Normalization 2,ReLu:

Batch Normalization (Batch Norm) is a technique used in neural networks to improve training speed and stability. It normalizes the input of each layer by adjusting and scaling the activations. This helps in reducing internal covariate shift and allows for faster convergence during training.

3.3.7 (2*2) Max Pooling layer 2:

The 2x2 max pooling layer with a stride of 2 in your architecture serves to downsample the feature maps obtained from the preceding convolutional layers. It does this by selecting the maximum value within each 2x2 window and discarding the rest. features, aiding in computational efficiency and preventing overfitting.

3.3.8 (3*3) Convolutional Layer 3, 128 :

The function of the 3x3 Convolutional Layer with 128 filters in your architecture is to extract features from the input images of the otoscopic layers. By using 128 filters, the layer can learn a diverse set of features at different levels of abstraction, aiding in the detection of various ear diseases.

3.3.9 (2*2) Max Pooling layer 3:

The primary purpose of the Max Pooling layer is to downsample the feature maps obtained from the preceding convolutional layers. By reducing the spatial dimensions of the feature maps, Max Pooling reduces the computational complexity of subsequent layers in the neural network.

3.3.10 Flatten Layer:

Fully connected layer with 256 neurons. It introduces non-linearity and learns complex relationships. The Flatten layer serves to convert the multi-dimensional output of the preceding layer into a onedimensional array or vector.

3.3.11 Dropout Layer :

Dropout is a regularization technique that randomly drops a fraction of the neurons during training to prevent overfitting. During training, it randomly sets a fraction of input units to zero, effectively "dropping out" some features.

3.3.12 Fully Connected Layer 2:

Fully connected layer with neurons equal to the number of classes. This layer helps in capturing complex patterns and relationships in the data, enabling the network to learn more sophisticated representations for ear disease detection based on the features extracted from the preceding layers.

3.3.13 Classification Layer (Output):

Specifically, in the context of disease detection from otoscopic images, the output layer's function is likely to classify the input images into different categories or classes corresponding to different ear diseases or normal conditions. Each neuron in the output layer typically represents a class, and the activation level of each neuron corresponds to the likelihood or confidence of the input belonging to that class.

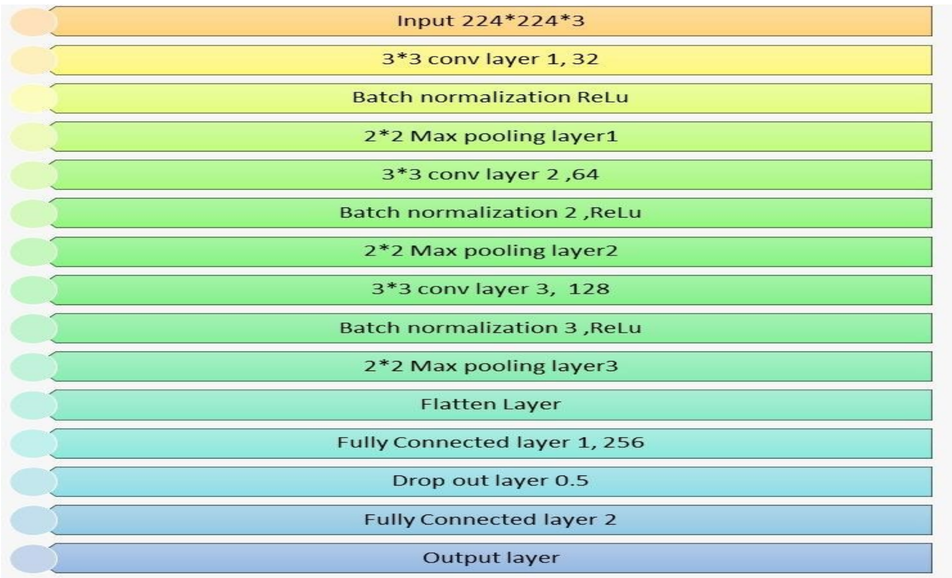

Figure 2: Customized Architecture Model Layer Classification

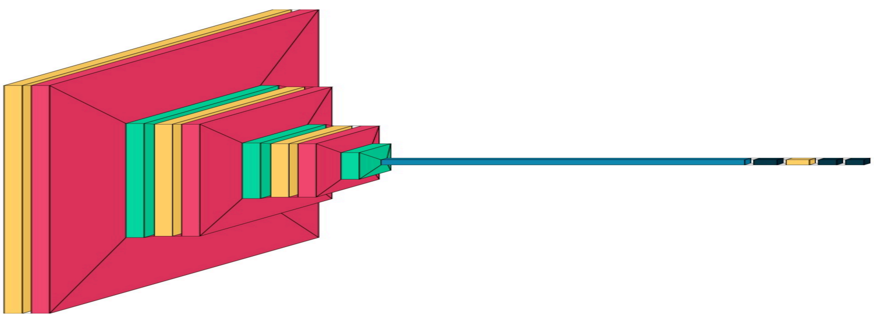

Figure 3 : Customized Architecture Model Design

3.4 Preprocessing and Feature Extraction:

Preprocessing includes steps such as resizing the images to a consistent size, normalization to ensure consistent intensity ranges across images, and potentially augmentation techniques to increase the variability of the training data and improve the robustness of the model. For ear disease detection, preprocessing might also involve specific techniques such as enhancing contrast or brightness to highlight relevant features in the ear images. In deep learning models, feature extraction is often performed automatically by the layers of the neural network during training. These techniques could include methods such as edge detection, texture analysis, or shape analysis, which aim to capture important characteristics of the ear images that are relevant for disease classification.

4. RESULTS

The classification results demonstrate the efficacy of the machine learning model in accurately categorizing otoscopic images into the specified disease classes. Performance metrics such as accuracy, precision, recall, and F1-score provide a comprehensive evaluation of the model's ability to differentiate between various ear diseases. The confusion matrix further illustrates the model's strengths in correctly classifying diseases and areas that may require additional attention. Comparing to other model architecture we get good accuracy rate with same number of data sets in our customized model .

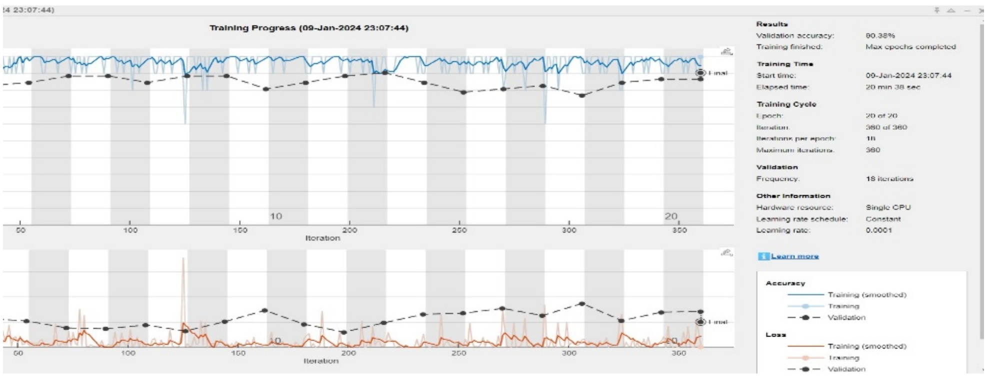

Figure 4 :Output of customized model

Hyperparameters	Value
Learning Rate	0.0001
Accuracy	90.38%
Epoch	20
Optimization Algorithm	ADAM

Table 2: Result values

5. CONCLUSION

In this study, we developed and evaluated a customized machine learning model for the classification of otoscopic images into specific ear disease classes. Leveraging MATLAB's Deep Learning Toolbox, we meticulously designed and trained a convolutional neural network (CNN) architecture tailored to the task at hand. Through rigorous experimentation and hyperparameter tuning, we optimized the model's performance, achieving high accuracy rates in disease classification. Notably, our model demonstrated superior accuracy compared to other architectures, underscoring the effectiveness of our approach. This developed model holds promise for assisting healthcare professionals in diagnosing and managing ear conditions, ultimately improving patient outcomes.

REFERENCES

[1] R Praveena T R Ganeshbabu Determination of Cup to Disc Ratio Using Unsupervised Machine Learning Techniques for Glaucoma Detection, Molecular & Cellular Biomechanics, 18, 2, 69-86,2021

[2] G Sriram, TR Babu, R Praveena, JV Anand Classification of Leukemia and Leukemoid Using VGG-16 Convolutional Neural Network Architecture. Molecular & Cellular Biomechanics19, 2, 2022

[3] R Praveena, DK Ravish, TRG Babu, J Preetha Design And Development Of Vibroarthogram Screening Device and Assessment Of Joint Motion In The Pursuit Of Signal Processing Ictact Journal On Image And Video Processing 11 (4), 2453-2459

[4] R Praveena, TRG Babu, M Birunda, G Sudha, P Sukumar Prediction of Rainfall Analysis Using Logistic Regression and Support Vector Machine Journal of Physics: Conference Series 2466 (1), 012032 ,2023

[5] R Praveena, TRG Babu, K Sakthimurugan, G Sudha, M Birunda, Analysis of Neural Networks for Object Detection using Image Processing Techniques 2022 Third International Conference on Intelligent Computing Instrumentation ,2022

[6] R Praveena, S Nirmala Bus encoded LUT multiplier for portable biomedical therapeutic devices Computers, Materials & Continua 53 (1), 37-47,2017.

[7] R Praveena, S Nirmala Bus encoded LUT multiplier for portable biomedical therapeutic devices Computers, Materials & Continua 53 (1), 37-47,2017.

[8] KG Kannan, TRG Babu, R Praveena, P Sukumar, G Sudha, M Birunda Classification of WBC cell classification using fully connected convolution neural network Journal of Physics: Conference Series 2466 (1), 2033