Ear Disease Detection By Otoscopic Images Using Matlab

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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.

I. INTRODUCTION

Ear infections affect millions of people worldwide, of all ages, and provide serious health risks. Effective management and treatment of many disorders depend on a prompt and correct diagnosis. Convolutional neural networks (CNNs), in particular, are deep learning techniques that have become highly effective tools for medical image analysis in recent years. They have the ability to automate illness identification procedures with great efficiency and accuracy. In this work, we utilise the ADAM optimisation method in conjunction with a customised CNN architecture to create a deep learning model for the automatic identification of ear disorders from otoscopic pictures. We want to solve the issues with manual diagnosis, such as subjectivity and interpretation variability, by utilising deep learning and image processing techniques.

1.1 Contributions and Major Issues Addressed

This work's main contribution is the creation of a reliable and precise deep learning model designed especially for the identification of ear diseases. We aim to gain better performance in illness classification tasks by adjusting the CNN architecture and fine-tuning model parameters with the ADAM optimizer. Furthermore, by using data augmentation approaches, the model becomes more reliable in real-world applications by boosting its capacity to generalise across various datasets.

II. PROPOSED METHOD

The training dataset is more diverse because to the innovative data augmentation techniques introduced by the suggested system. This enhances the model's capacity to manage otoscopic picture fluctuations, strengthening its resistance to difficulties caused by a lack of annotated medical images. To offer a more thorough evaluation of the model's efficacy, performance indicators and assessment procedures are improved. To ensure a full grasp of the model's advantages and shortcomings, more metrics could be included.

2.1 Phases of Proposed work

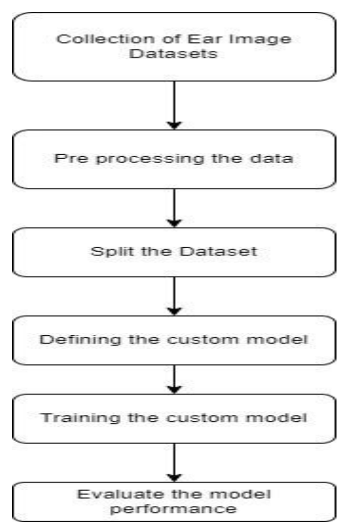

Figure 1: Flowchart of phases of proposed work

2.2 REVIEW OF LITERATURE

2.2.1 Diagnosis of Ear conditions using Deep Learning approach[6]

Itdescribes 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[8]

Itdescribes 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[11]

It 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[12]

It 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[13]

It 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.

III. EASE OF USE

3.1Disease Classification

Our machine learning-based system's classification of ear disorders is a vital component. Every illness is identified by examining certain patterns found in otoscopic pictures, with an emphasis on the state of the tympanic membrane. The following illnesses are covered by the categorization system:

- 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 from many hospitals and from open source tools, 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 For Ear Disease Detection:

3.3.1 Input Layer 224*224*3:

The image input sizes are specified by this layer. It anticipates 224 x 224 pixel images with three RGB colour channels. The input layer is where your photos enter your neural network design for the first time.

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

Convolutional layer including 32 filters and a 3x3 filter size. In order to preserve the input's spatial dimensions, "Padding" is set to "same." A convolutional layer is essential for extracting features. In order to identify different patterns and features, including edges, textures, and shapes, it runs a number of filters on the input data, which in your instance is photos of the ear canal.

3.3.3 Batch Normalization ReLu:

In order to normalise the inputs of every layer in a mini-batch of data, the batch normalisation layer is essential.

3.3.4 (2*2) Max Pooling layer 1:

By choosing the maximum value in each zone, max pooling lowers spatial dimensions and helps with dimensionality reduction and feature extraction. The purpose of the 2x2 max pooling layer in your MATLAB ear illness detection project is to downsample the feature maps that were acquired from the earlier convolutional layers.

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

The term "convolutional layer" designates a layer that uses 3x3 filters to conduct convolutions. A filter, sometimes referred to as a kernel, slides across the input data during convolution, a basic CNN process, multiplying the data element-by-element and adding the results to create a feature map.

2*64 This shows that 3x3 filters are used by the layer to perform convolutions. A filter, sometimes referred to as a kernel, slides across the input data during convolution, a basic CNN process, multiplying the data element-by-element and adding the results to create a feature map.

3.3.6 Batch Normalization 2,ReLu:

Neural networks use the batch normalisation (Batch Norm) technique to increase training speed and stability. It does this by scaling and modifying the activations of each layer to normalise the input. This facilitates quicker convergence during training and lessens internal covariate shift.

3.3.7 (2*2) Max Pooling layer 2:

In our design, the 2x2 max pooling layer with a stride of 2 is used to downsample the feature maps that are acquired from the previous convolutional layers. In order to reduce overfitting and increase computational performance, it accomplishes this by choosing the maximum value within each 2x2 window and eliminating the remaining features.

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

In our architecture, the 3x3 Convolutional Layer with 128 filters is used to extract features from the otoscopic layers' input images. The layer can detect a variety of ear ailments by using 128 filters, which let it to learn a broad range of features at various levels of abstraction.

3.3.9 (2*2) Max Pooling layer 3:

The feature maps acquired from the previous convolutional layers are downsampled as the main function of the Max Pooling layer. Max Pooling lowers the computational complexity of the neural network's later layers by shrinking the spatial dimensions of the feature maps.

3.3.10 Flatten Layer:

256-neuron fully linked layer. It teaches complicated relationships and introduces non-linearity. The multi-dimensional output of the previous layer is transformed into a one-dimensional array or vector by the flatten layer.

3.3.11 Dropout Layer :

In order to avoid overfitting, dropout is a regularisation strategy that randomly removes a portion of the neurons during training. By "dropping out" some features, it randomly sets a portion of the input units to zero during training.

3.3.12 Fully Connected Layer 2:

Layer that is fully linked and has the same number of neurons as classes. Using the features that were taken out of the previous layers, this layer assists in identifying intricate patterns and relationships in the data, allowing the network to learn more complicated representations for the diagnosis of ear diseases.

3.3.13 Classification Layer (Output):

More specifically, the job of the output layer in the context of illness identification from otoscopic pictures is probably to classify the input images into several categories or classes corresponding to various ear disorders or normal situations. The activity level of each neuron in the output layer, which typically represents a class, reflects the probability or confidence that the input belongs to that class.

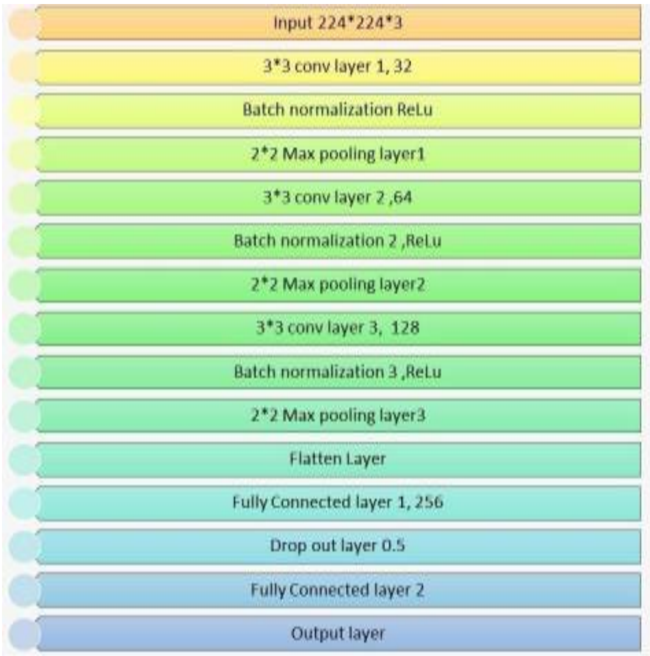

Figure 2: Customized Architecture Model Layer Classification for Ear Disease Detection

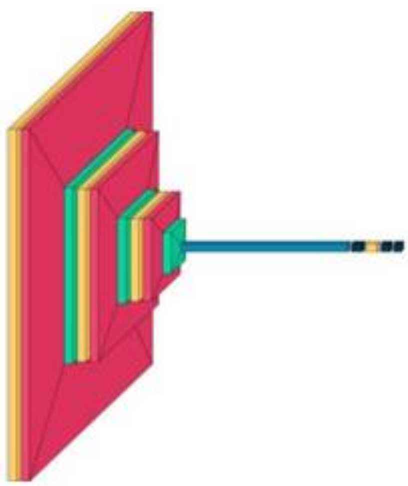

Figure 3 : Customized Architecture Model Design For Ear Disease Detection

3.4 Preprocessing and Feature Extraction:

Preprocessing entails actions like shrinking the photos to uniform sizes, normalising the images to guarantee uniformity in theintensity ranges, and maybe applying augmentation techniques to boost the training data's variability and strengthen the model's resilience. Preprocessing may also entail particular methods, such as boosting contrast or brightness to draw attention to pertinent details in the ear pictures, in order to diagnose ear diseases. The layers of the neural network generally carry out feature extraction automatically during training in deep learning models. These approaches could involve techniques like edge identification, texture analysis, or shape analysis, which seek to identify crucial elements of the ear pictures that are pertinent to the classification of diseases.

IV. RESULTS

The outcomes of the classification shows how well the machine learning model performs in precisely classifying otoscopic pictures into the designated illness classifications. Performance measures including recall, accuracy, precision, and F1-score offer a thorough assessment of the model's capacity to distinguish between different ear conditions. The model's accuracy in detecting diseases and areas that could need more attention is further demonstrated by the confusion matrix. With the same number of data sets, our customised model yields a good accuracy rate when compared to alternative model architectures.

Figure 4 :Output of customized model

Table 2: Result values

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

V. CONCLUSION

In this work, a customized machine learning model for classifying otoscopic pictures into several ear disease classifications was constructed and assessed. We carefully planned and trained a convolutional neural network (CNN) architecture that was appropriate for the task at hand by utilising MATLAB's Deep Learning Toolbox. We achieved high accuracy rates in disease categorization by optimizing the model's performance through extensive experimentation and hyperparameter adjustment. Notably, our model outperformed rival architectures in accuracy, highlighting the efficacy of our methodology. This developed model has the potential to improve patient outcomes by helping medical practitioners diagnose and treat ear problems.

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, 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

[4] Moberly AC, Zhang M, Yu L, Gurcan M, Senaras C, Teknos TN, et al. Digital otoscopy versus microscopy: How correct and confident are ear experts in their diagnoses?, 24; 2018

[5] Kingma DP, Ba J. Adam: A method for stochastic optimization. arXiv Preprint 2014 arXiv:1412.6980

[6] A. Singh and M. K. Dutta, "Diagnosis of Ear Conditions Using Deep Learning Approach," 2021 International Conference on Communication, Control and Information Sciences (ICCISc), Idukki, India, 2021, pp. 1-5, doi: 10.1109/ICCISc52257.2021.9484919.

[7] Sandler M, Howard A, Zhu M, Zhmoginov A, Chen L-C. Mobilenetv2: Inverted residuals and linear bottlenecks. Proceedings of the IEEE conference on computer vision and pattern recognition; 2018. p. 4510–20.

[8] Byun, H.; Yu, S.; Oh, J.; Bae, J.; Yoon, M.S.; Lee, S.H.; Chung, J.H.; Kim, T.H. An Assistive Role of a Machine Learning Network in Diagnosis of Middle Ear Diseases. J. Clin. Med. 2021, 10, 3198. https://doi.org/10.3390/jcm10153198

[9] Marom T, Kraus O, Habashi N, Tamir SO. Emerging technologies for the diagnosis of otitis media. Otolaryngol Head Neck Surg 2019;160:447–56.

[10] He K, Zhang X, Ren S, Sun J. Deep residual learning for image recognition. Proceedings of the IEEE conference on computer vision and pattern recognition; 2016. p. 770–778

[11] Kandaswamy, Manju & Muthan, Paramasivam & Nagarjun, S. & Mokesh, A. & Abishek, A. & Meialagan, K.. (2022). Deep Learning Algorithm for Identification of Ear Disease. 10.1007/978-981-16-5120-5_37.

[12] Khan MA, Kwon S, Choo J, Hong SM, Kang SH, Park IH, Kim SK, Hong SJ. Automatic detection of tympanic membrane and middle ear infection from oto-endoscopic images via convolutional neural networks. Neural Netw. 2020 Jun;126:384-394.doi: 10.1016/j.neunet.2020.03.023. Epub 2020 Apr 1. PMID: 32311656.

[13] Cha D, Pae C, Seong SB, Choi JY, Park HJ. Automated diagnosis of ear disease using ensemble deep learning with a big otoendoscopy image database. EBioMedicine. 2019 Jul;45:606-614. doi: 10.1016/j.ebiom.2019.06.050. Epub 2019 Jul 1. PMID: 31272902; PMCID: PMC6642402.