Fusion-Based Model for Detection of Middle Ear Infections

Submitted in partial fulfillment for the award of the degree of

Bachelor of Technology in ComputerScience and Engineering

By

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May, 2024

DECLARATION

I here by declare that the thesis entitled "**FUSION-BASED MODEL FOR DETECTION OF MIDDLE EAR INFECTIONS**" submitted by me, for the award of the degree of Bachelor of Technology in Computer Science andEngineering, Vellore Institute of Technology, Vellore, is a record of bonafide work carried out by me under the supervision of DR. NIHA K

I further declare that the work reported in this thesis has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university.

Place: Vellore

Date:

Signature of the Candidate

CERTIFICATE

This is to certify that the thesis entitled **"FUSION-BASED MODEL FOR DETECTION OF MIDDLE EAR INFECTIONS"** submitted by **MD DANISH ANWAR (20BCE0106), YUVRAJ SINGH (20BCI0242) & NABIL ASHRAF (20BCI0279) to** Vellore Institute of Technology, Vellore, in partial fulfillment of the requirementfor the award of the degree of **Bachelor of Technology in Computer Science andEngineering** programme is a bonafide record carried out under **Dr. NIHA K** guidance. The project fulfills the requirements as per the regulations of this University and in myopinion meets the necessary standards for submission.

The contents of this reporthave not been submitted and will not be submitted either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university. The thesis fulfills the requirements and regulations ofthe University and in my opinion meets the necessary standards for submission.

Place : Vellore

Date :

Signature of the Guide

Internal Examiner **External Examiner**

HOD
Computer Science and Engineering

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I would like to acknowledge that this project was completed entirely by me and by my colleague.

MD DANISH ANWAR
YUVRAJ SINGH
NABIL ASHRAF

Executive Summary

The study proposes a novel approach for diagnosing ear drum infections (AOM) using advanced machine learning models and Fusion methodology. By combining a VGG19 CNN model for otoscope image analysis with a random forest classifier for tympanometry data, the method aims to improve accuracy in diagnosis, especially crucial in young children who may struggle to communicate symptoms. The random forest classifier identifies peak values in tympanograms indicative of infection presence. Results show enhanced accuracy in diagnosing AOM, promising earlier detection and treatment, crucial for preventing complications like hearing loss. This approach represents a significant advancement in medical diagnostics, offering potential to revolutionize AOM diagnosis and treatment, ultimately leading to improved patient outcomes and reduced healthcare costs. By integrating multiple data sources, the proposed method showcases substantial potential in improving patient care, marking a significant milestone in the field of medical diagnostics.

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List of Abbreviations

AOM	ACUTE OTITUS MEDIA
EAC	EXTERNAL AUDITORY
ME	MIDDLE EAR
TM	TYMPANIC MEMBER
VGG19	VISUAL GEOMETRY GROUP

1. INTRODUCTION

1.1 Introduction to the Project Domain

The EAC canal (EAC) and ME are separated anatomically by the tympanic membrane (TM). It is in charge of gathering sound from the auricle and EAC and delivering that sound via mechanical vibration to the ossicles and cochlea. A ME infection, also known as otitis media, is a condition where the ME becomes inflamed and infected as shown in the Fig.1. The ME is located behind the ear drum and contains tiny bones that transmit sound from the outer ear to the inner ear.

ME infections are typically caused by bacteria or viruses and can occur in both children and adults. Common symptoms include ear pain, fever, difficulty hearing, and a feeling of pressure or fullness in the ear. Treatment for a MEinfection may involve antibiotics to clear the infection and pain medication to relieve discomfort. In some cases, a procedure called a myringotomy may be necessary, where a small incision is made in the ear drum to drain fluid from the middle ear. Risk factors for ME infections include a history of ear infections, allergies, exposure to secondhand smoke, and attending daycare or school where there is a higher risk of exposure to viruses and bacteria.

If left untreated, ME infections can lead to complications such as hearing loss, a ruptured ear drum, or the spread of infection to nearby structures such as the mastoid bone. It is important to seek medical attention if you suspect you or your child may have a ME infection.

In order to determine the location of a patient's ear condition, it is important to consider whether the issue is related to the external ear, middle ear, or inner ear. To help localize the issue, a thorough physical examination of the patient's ear is necessary. If the examination reveals that the outer ear, EAC canal, and tympanic membrane appear normal, this may indicate that the lesion could be located either in the ME or inner ear.

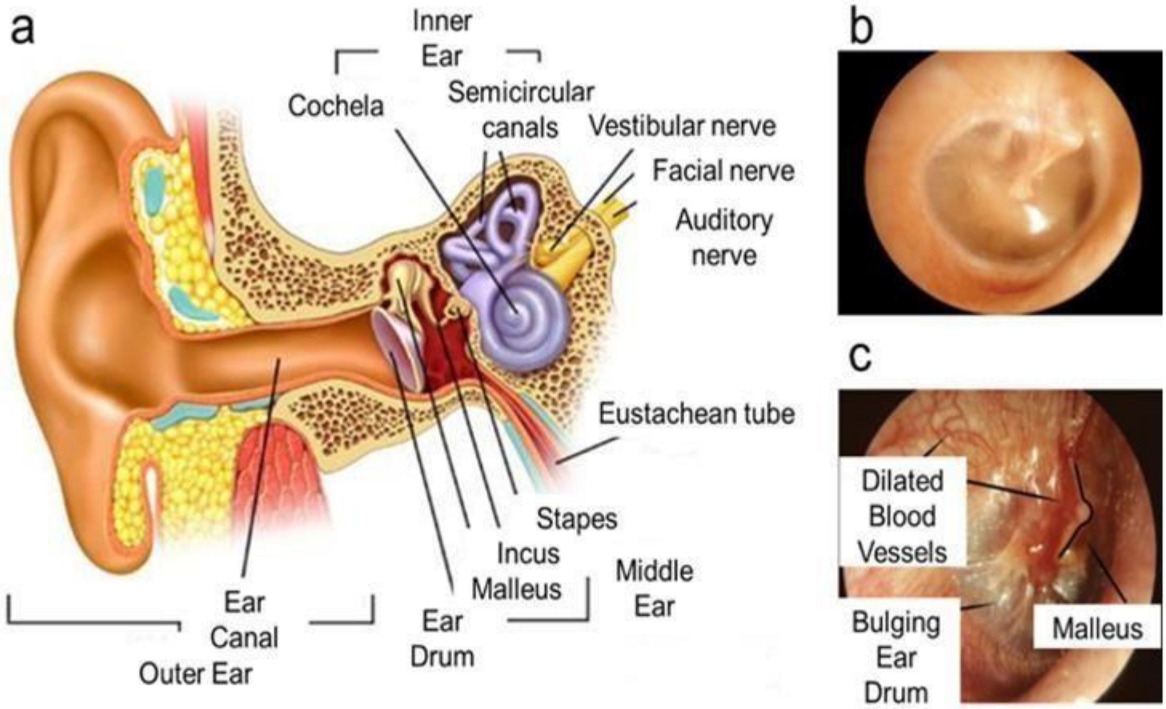


Fig.1 (Anatomy) Copyright Microbiology Society, 2015.

1.2 Aim of the Project

The primary aim of this project is to develop and validate a novel diagnostic method for accurately detecting Middle Ear (ME) infections by integrating otoscopic images and tympanometry findings using advanced CNN models and machine learning algorithms. Specifically, the project aims to employ the VGG19 model for precise image analysis and the Random Forest model for comprehensive Tympanometry analysis, creating a methodology that is both highly accurate and accessible to non-specialist healthcare providers.

Through the utilization of decision fusion methodology to integrate the outputs of these two models, the project aims to deliver a final diagnosis that is significantly more precise and reliable. By harnessing the strengths of advanced image analysis techniques and machine learning algorithms, the proposed method seeks to notably enhance the diagnosis and treatment of otitis media, particularly among individuals who may lack access to specialized ENT care.

Additionally, the project endeavors to improve the efficiency of diagnostic processes and reduce the need for unnecessary referrals to specialists. Ultimately, the aim is to provide a more effective and efficient means of diagnosing ear infections, ultimately leading to improved health outcomes for patients.

1.3 Objectives of the Project

The main objective of this project is to develop a pioneering method for accurately detecting Middle Ear (ME) infections by combining otoscopic images and tympanometry findings using cutting-edge CNN models and advanced machine learning algorithms. Specifically, we will utilize the VGG19 model for thorough image analysis and the Random Forest model for comprehensive Tympanometry analysis. This combination of techniques aims to create a diagnostic approach that is highly precise and accessible even to healthcare professionals without specialized training.

Through the implementation of decision fusion methodology to merge the results of these two models, we expect to achieve a final diagnosis that is significantly more accurate and reliable. This innovative approach leverages the strengths of advanced image analysis techniques and machine learning algorithms to improve the diagnosis and subsequent treatment of otitis media, particularly for individuals lacking access to specialized ENT care.

Furthermore, our method has the potential to streamline diagnostic processes, reducing the need for unnecessary referrals to specialists and ultimately enhancing overall healthcare efficiency. By offering a more effective and efficient means of diagnosing ear infections, our aim is to contribute to better health outcomes for patients by ensuring timely and appropriate treatment interventions.

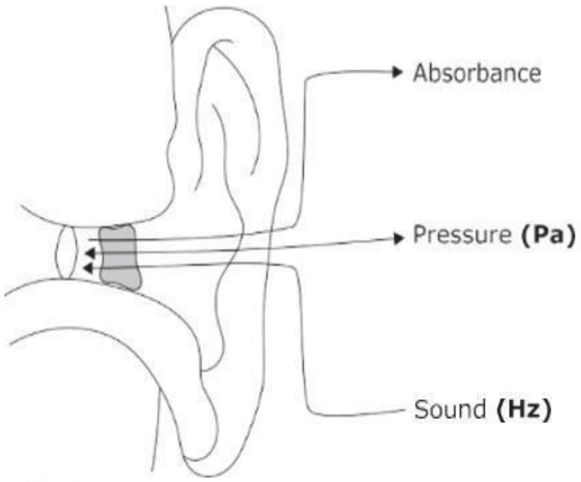


Fig. 2. Tympanometry device simulation to eardrum

1.4 Scope of the Project

Enhanced Diagnostic Precision: The integration of both tympanometry and otoscopic image processing within the combined model offers medical practitioners a more comprehensive dataset, potentially elevating the accuracy of ear infection diagnoses. This advancement holds the promise of delivering more effective and timely treatments, thereby mitigating the likelihood of complications and enhancing patient outcomes.

Expedited Diagnosis: Armed with the combined model, healthcare professionals can swiftly and precisely determine the nature of a patient's ear infection, facilitating prompt administration of suitable treatments. This accelerated diagnostic process holds the potential to minimize patient wait times for diagnosis, enhancing overall patient satisfaction and alleviating strain on healthcare infrastructures.

Improved Accessibility: In regions where access to specialized ENT expertise and diagnostic equipment may be scarce, the development of a unified model that integrates both tympanometry and otoscopic image analysis could prove transformative. By equipping medical practitioners in such areas with enhanced diagnostic capabilities, this innovation has the potential to improve the accuracy of diagnoses and enhance patient care standards, even in resource-constrained environments.

1.5 Organization of the Thesis

The proposed model is designed to automatically detect infections in the Middle ear (ME) using cutting-edge CNN models, such as VGG19. To achieve this, the model utilizes two main modules: the VGG19 module and the random forest module. The VGG19 module is responsible for analyzing otoscopic images to identify any ear abnormalities. The model uses transfer learning to train VGG19 on a large dataset of otoscopic images to improve its performance in detecting ME infections accurately.

The random forest module, on the other hand, analyzes tympanometry data, which is collected from the clinical guide using tympanogram peak values. This module is trained to classify ME infections using a random forest classifier. The classifier uses the collected tympanometry data to identify patterns and generate predictions regarding the presence and severity of ME infections.

To increase the accuracy of diagnoses, the model employs the fusion methodology, which combines the outputs from the VGG19 module and the random forest module. This process combines the predictions made by the two modules to provide a more accurate and reliable diagnosis of ME infections.

The proposed model's architecture is highly sophisticated, combining the strengths of both deep learning and machine learning algorithms. By using transfer learning, the VGG19 module can achieve high accuracy in detecting ear abnormalities, while the random forest module can analyze tympanometry data accurately. The fusion methodology combines the outputs from both modules to provide highly accurate diagnoses that can be used by non-ENT doctors and specialists alike.

Overall, the proposed model offers a highly innovative approach to the detection of ME infections, which can be challenging for non-ENT doctors to identify accurately. The model combines the strengths of deep learning and machine learning algorithms to achieve highly accurate diagnoses, making it an invaluable tool for healthcare providers in the accurate identification and treatment of ME infections.

2. LITERATURE REVIEW

2.1 Survey on Existing System

PAPER TITLE	AUTHORS	METHODOLOGY	TECHNIQUE
Inter-rater reliability of the diagnosis of otitis media based on otoscopic images and wideband tympanometry measurements	Sundgaard, J. V., Värendh, M.,Nordström,F., Kamide,Y.,Tanaka, C., Harte, J., ...&Laugesen, S. (2022)	The study aimed to investigate the inter-rater reliability and agreement of the diagnosis of otitis media witheffusion, acute otitis media, and no effusion cases based on otoscopy images and, in some cases, additional wideband tympanometry (WBT) measurements.	Percentage of agreement and kappa statistic
Few-Shot Wideband Tympanometry Classification in Otosclerosis via Domain Adaptation with Gaussian Processes	Nie, L., Li, C., Bozorg Grayeli, A., & Marzani, F. (2021)	A deep transfer learning solution was adopted to perform Wideband tympanometry (WBT) classification for automatic diagnosis of otosclerosis under the constraint of limited labeled WBT data. The source dataset was synthesized by data augmentation.	Gaussian Processes - Guided Domain Adaptation (GPGDA) Algorithm, Fine-Tuning (FT) method, CNN,deep adaptation networks (DAN), deep transfer learning methods

Deep metric learning for otitis media classification	Sundgaard, J. V., Harte, J., Bray, P., Laugesen, S., Kamide, Y., Tanaka, C., ... & Christensen, A. N. (2021)	This study introduces an automated diagnostic algorithm for identifying otitis media using otoscopy images of thetympanic membrane. Through assessment by a medical specialist, 1336 images were categorized into three diagnostic groups: acute otitis media, otitis media with effusion,and no effusion. Accurate detection of tympanic membrane abnormalities is crucial for appropriate treatment and reducing unnecessary antibiotic usage.	Deep Metric Learning, Convolutional neural network , Image Classification
OtoPair: Combining Right and Left Eardrum Otoscopy Images to Improve the Accuracy of Automated Image Analysis	Camalan, S.; Moberly, A.C.; Teknos, T.; Essig, G.; Elmaraghy, C.; Taj-Schaal, N.; Gurcan, M.N. (2021)	Researchers aimed to classify eardrums as normal, containing fluid (effusion), or having a tympanostomy tube, using image analysis. Due to limited data, they focused on a simplified approach: distinguishing normal from abnormal eardrums. A total of 300 individual eardrum images were divided into normal and abnormal categories (effusion or tube). Special programs were trained on these images to learn visual patterns associated with each category.	Transfer based learning feature extraction Image Processing
Diagnosis, Treatment, and Management of Otitis Media with Artificial Intelligence	Ding, X., Huang, Y., Tian, X., Zhao, Y., Feng, G.,Gao, Z. (2023)	The review explores the challenges in diagnosing and treating otitis media (OM)and discusses the potential applications ofartificial intelligence (AI) and machine learning (ML) in addressing these challenges. It introduces important concepts related to ML and AI and describes howthese technologies are currently being utilized for diagnosing, treating, and managing OM.	Natural language processing (NLP), Convolutional neural networks (CNN), Computer vision (CV)

Detection of Otitis Media With Effusion Using In-Ear Microphones and Machine Learning	Kuan-Chung Ting; Syu-Siang Wang; You-Jin Li;Chii-Yuan Huang; Tzong-Yang Tu; Chun-Che Shih; Kai-Chun Liu (2023)	The study proposes an Otitis Media with Effusion (OME) detection system utilizingin-ear microphones and machine learning (ML) techniques to support clinicians in diagnosis. The system records user voicesusing in-ear microphones, then extracts acoustic features through short-time Fourier transform (STFT). ML classifiers are employed to estimate the health status of the middle ear, with weighted-threshold postprocessing applied. The developed approach is cost-effective, user-friendly, and aims to provide objective assistance to clinicians for detecting and identifying OMEin home-based environments.	Short-Time Fourier transform (STFT), ML Classification MODELS: SVM, GNB, AdaBoost, RF, and CNN classification models.

2.2 Gaps Identified

Our study encountered numerous challenges during the implementation of our methodology for detecting Middle Ear (ME) infections. Among the most notable obstacles was ensuring both the quality and quantity of the data utilized to train and test our machine learning models were sufficient. Acquiring medical imaging data can prove challenging, and the subjective nature of image interpretation compounded this difficulty. Additionally, obtaining precise tympanometry data from patients presented hurdles, as some individuals may experience discomfort during the procedure, leading to potential inaccuracies in the data.

While otoscopy and tympanometry serve as valuable diagnostic tools for otitis media, they may not always yield definitive results. Certain scenarios, such as difficulties discerning the presence of fluid in the middle ear solely through otoscopy or inconclusive tympanometry results, underscore the need for novel diagnostic methods that offer enhanced accuracy and reliability.

Another challenge we confronted was distinguishing between otitis media and ear drum infection, as both types of infections exhibit similar symptoms and imaging characteristics. Although our machine learning models could detect the presence of infection in the middle ear, discriminating between the two necessitated clinical examinations and additional tests, thus adding complexity to our methodology.

Ensuring the optimal performance of our machine learning models also proved challenging, as we grappled with concerns such as bias, overfitting, and instances of false positives/negatives. To mitigate these issues, we conducted model validation using independent datasets and assessed their sensitivity and specificity to verify their robustness and minimize potential biases.

2.3 Problem Statement

The term "otitis media" (OM) is used to describe inflammation of the middle ear, and each type of OM has a unique diagnosis. However, when it comes to diagnosing an ear infection, non-ENT experts may have varying levels of knowledge and experience. While an ENT expert may be able to predict the location of an ear infection through an otoscopic examination, they cannot accurately predict the severity of the infection. It is crucial to be able to identify eardrum abnormalities that a primary physician may not be able to detect, with the exception of an ENT specialist.

The underlying research paper claims that their method is unable to differentiate between various forms of otitis media because it can only detect ear abnormalities using automatic Wideband tympanometry in the ear. Therefore, the Fusion Methodology is used where possible to combine the two approaches, making it simpler for non-ENT doctors to specialists to diagnose OM. However, this approach also has its challenges, as it requires a sufficient quantity and quality of data to train and test machine learning models accurately. Additionally, collecting accurate tympanometry data from patients can be difficult, as some patients may experience discomfort during the procedure, leading to inaccuracies in the data.

Another challenge is addressing the performance of the machine learning models to avoid issues such as bias, overfitting, and false positives/negatives. To overcome these issues, the researchers validated their models using independent data sets and assessed their sensitivity and specificity to ensure that they performed well and were not affected by these issues. Finally, implementing this methodology in a clinical setting raised ethical and legal considerations. Collecting and processing the data required significant time and resources, and using machine learning models in clinical decision-making needed careful consideration.

Despite these challenges, the researchers believe that their methodology has the potential to improve the accuracy and efficiency of OM diagnoses. By identifying eardrum abnormalities that may go undetected by non-ENT specialists, their approach may aid in the diagnosis of

3. REQUIREMENT ANALYSIS

3.1 Requirements

3.1.1 Functional

1. **Otoscopic Image Analysis Module**:
   - The system should be able to process otoscopic images using the VGG19 CNN model.
   - It should accurately detect abnormalities in the ear indicative of middle ear infections (ME).
   - The module should provide classification results for ME infections based on otoscopic image analysis.
2. **Tympanometry Analysis Module**:
   - The system needs to collect and process tympanometry data.
   - It should utilize a Random Forest model to analyze tympanometry data and classify ME infections.
   - The module must generate predictions regarding the presence and severity of ME infections based on tympanometry.
3. **Decision Fusion Methodology**:
   - The system should combine outputs from the otoscopic image analysis and tympanometry modules.
   - It should utilize fusion methodology to create a final, more accurate diagnosis of ME infections.
   - The final diagnosis should consider the results from both modules to enhance precision and reliability.

3.1.2 Non-Functional

1. **Accuracy**:
   - The system should achieve a high level of accuracy in diagnosing ME infections, aiming for at least 90% accuracy.
   - It should provide reliable and consistent results to ensure effective diagnosis and treatment.
2. **Speed**:
   - The system should process otoscopic images and tympanometry data efficiently, minimizing processing time.
   - It should generate diagnoses promptly to facilitate timely medical intervention.
3. **Ease of Use**:

- The system should be user-friendly, allowing medical professionals to easily input data and interpret results.
- It should provide clear and intuitive visualizations of the diagnosis for easy understanding.

4. **Scalability**:
    - The system should be scalable to accommodate a growing dataset of otoscopic images and tympanometry data.

3.2 Feasibility Study

3.2.1 Technical Feasibility

1. **Hardware Requirements**:
    - The system will require standard computing hardware, including a CPU with sufficient processing power.
    - It should have adequate storage capacity to store the dataset of otoscopic images and tympanometry data.
    - A reliable internet connection may be necessary for data transfer and model updates.

3.2.2 Economic Feasibility

1. **Cost-Benefit Analysis**:
    - The system's development and implementation costs should be evaluated against the potential benefits.
    - Cost-effectiveness should be considered in terms of improved diagnosis accuracy and reduced treatment costs.
2. **Resource Availability**:
    - The availability of funding and resources for developing and maintaining the system should be assessed.
    - Potential cost-saving benefits from more accurate diagnoses and reduced referrals to specialists should be considered.

3.2.3 Social Feasibility

1. **User Acceptance:**
    - The system's usability and acceptance by medical professionals should be assessed through user testing and feedback.
    - Training programs may be necessary to ensure healthcare professionals are comfortable using the system.

2. Ethical Considerations:

- Ethical guidelines regarding patient data privacy and confidentiality must be adhered to.
- The system should comply with regulatory standards for medical devices and diagnostic tools.

3.3 System Specification

3.3.1 Hardware Specification

1. Computing Hardware:

- Processor: Intel Core i7 or equivalent
- Memory: 16GB RAM or higher
- Storage: Minimum 500GB SSD for data storage
- Display: High-resolution monitor for otoscopic image analysis

2. Internet Connectivity:

- Reliable high-speed internet connection for data transfer and updates
- Secure network infrastructure to ensure data integrity and confidentiality

3.3.2 Software Specification

1. Operating System:

- Compatible with Windows 10, macOS, or Linux distributions
- Ensure compatibility with required software libraries and frameworks (e.g., Python, TensorFlow, scikit-learn)

2. Development Tools:

- Python programming language for model development
- TensorFlow and Keras for CNN model development (VGG19)

- scikit-learn for Random Forest model development
- Jupyter Notebook or similar for data exploration and model training

3. **Database**:
   - SQLite or PostgreSQL for storing otoscopic images metadata and tympanometry data
   - Efficient querying and indexing for quick data retrieval and analysis

3.3.3 Standards and Policies

1. **Data Privacy and Security**:
   - Compliance with HIPAA regulations for patient data protection
   - Encryption protocols for secure data transmission and storage
2. **Model Training Standards**:
   - Follow best practices for model development, including data preprocessing, cross-validation, and hyperparameter tuning
   - Document model architecture, training methodology, and validation procedures for reproducibility

1. PROJECT DESCRIPTION

1.1 System Architecture

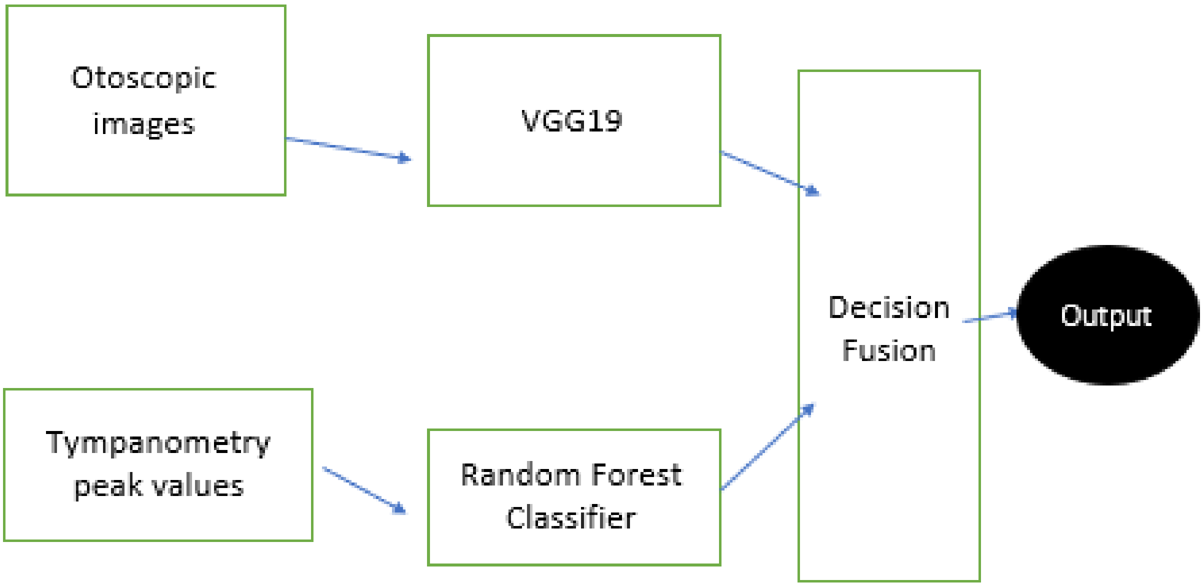


Fig.3. Basic proposed model architecture

1.2 Design

1.2.1. Data Flow Diagram

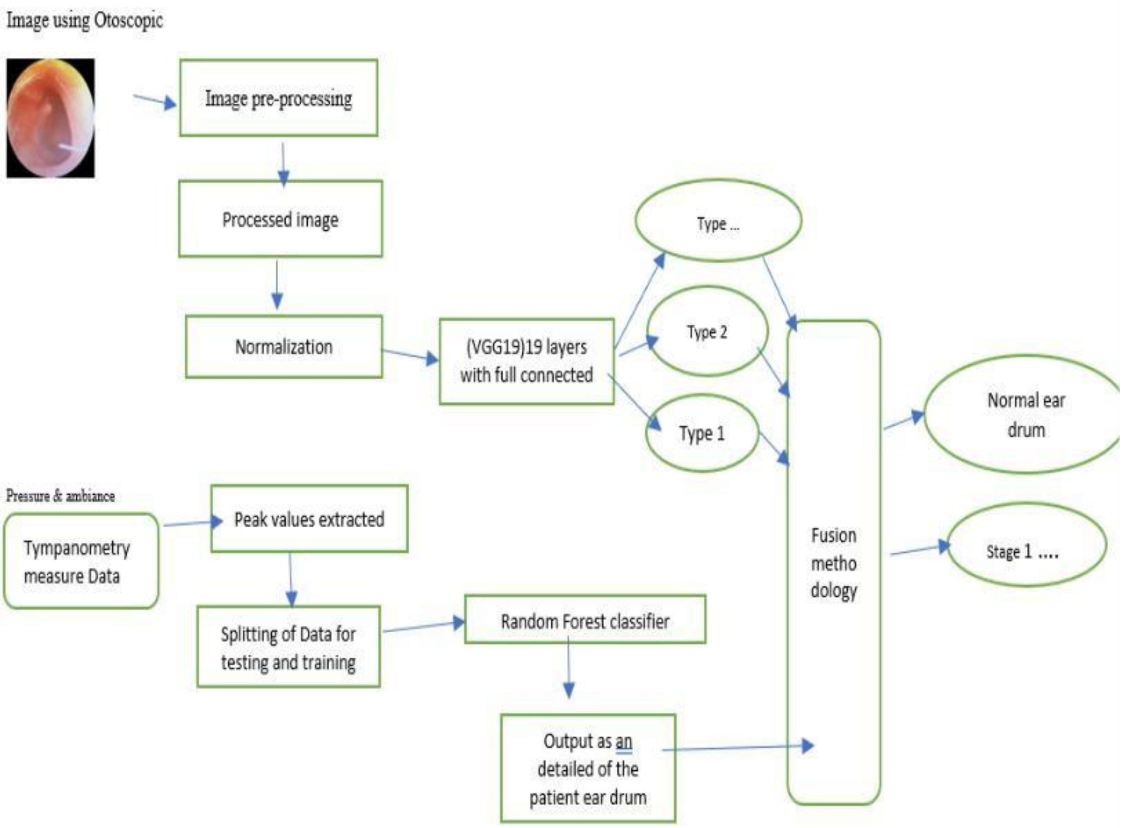
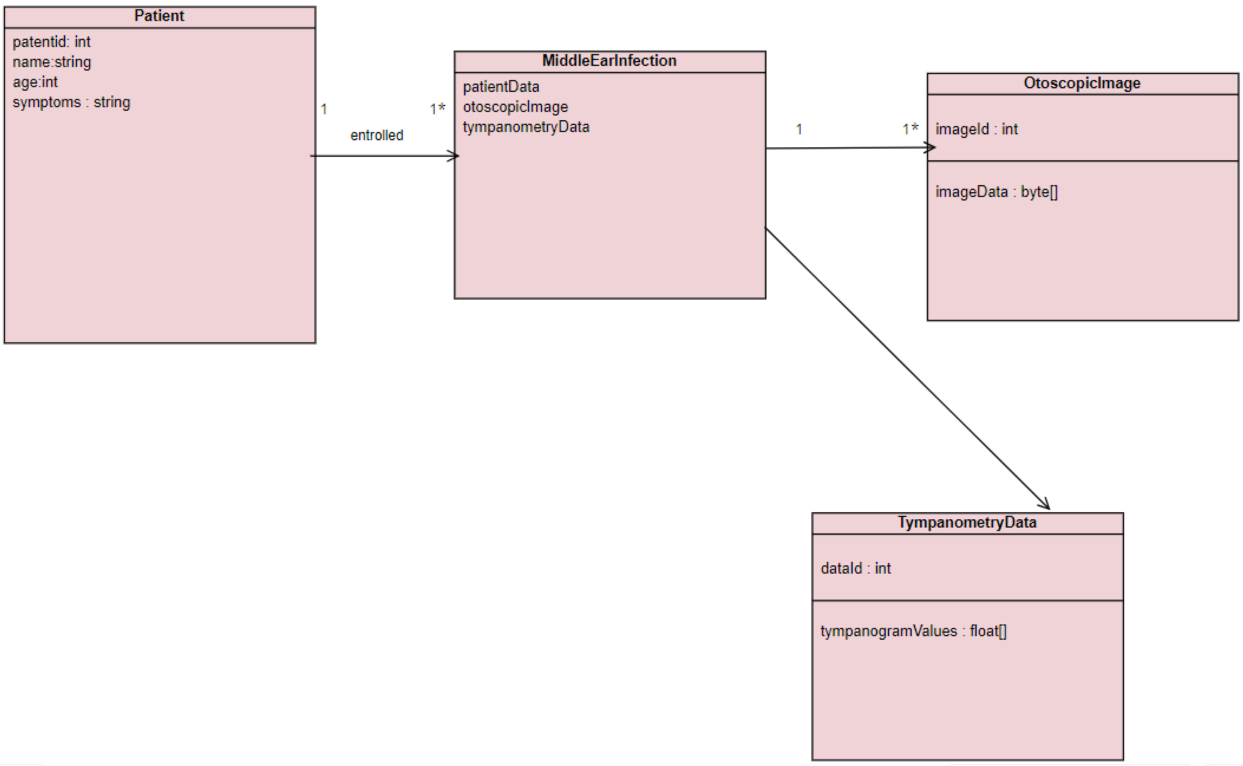
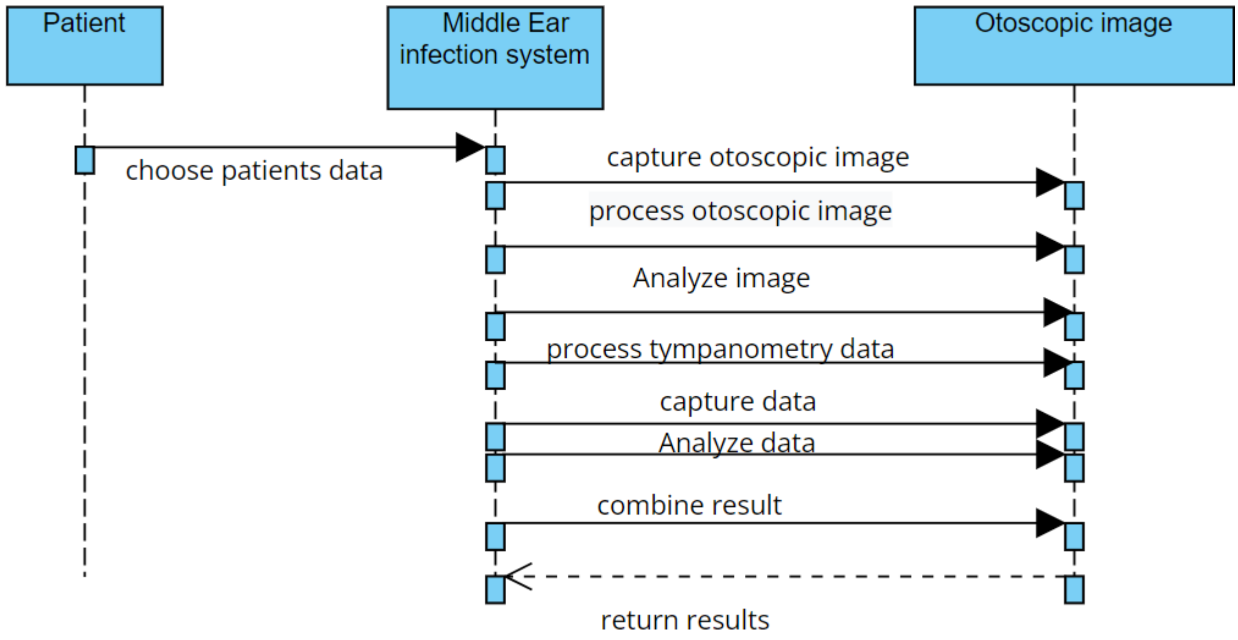


Fig: the proposed model Flow Diagram

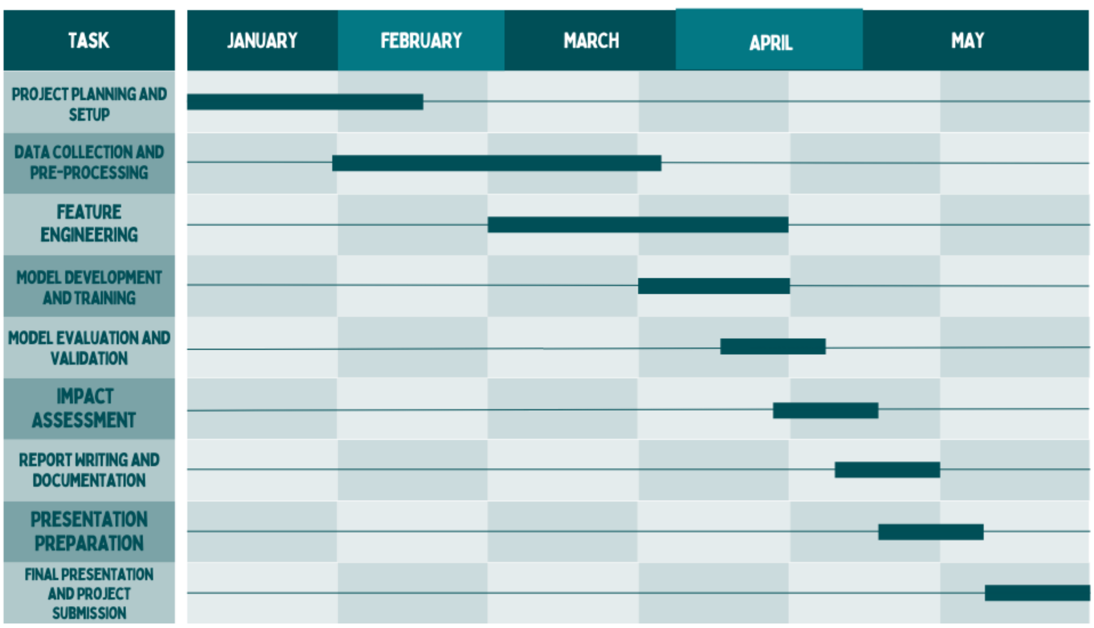
1.2.2 Class Diagram



1.2.3 Sequence Diagram


Patient
Middle Ear infection system
Otoscopic image
choose patients data
capture otoscopic image
process otoscopic image
Analyze image
process tympanometry data
capture data
Analyze data
combine result
return results

GANTT CHART


TASK
JANUARY
FEBRUARY
MARCH
APRIL
MAY
PROJECT PLANNING AND SETUP
DATA COLLECTION AND PRE-PROCESSING
FEATURE ENGINEERING
MODEL DEVELOPMENT AND TRAINING
MODEL EVALUATION AND VALIDATION
IMPACT ASSESSMENT
REPORT WRITING AND DOCUMENTATION
PRESENTATION PREPARATION
FINAL PRESENTATION AND PROJECT SUBMISSION

1.3 Module Description

1.3.1 VGG19 model

The VGG19 model is a convolutional neural network architecture that was proposed by Karen Simonyan and Andrew Zisserman in their paper "Very Deep Convolutional Networks for Large-Scale Image Recognition." It is an extension of the VGG16 model, with additional convolutional layers.

Introduction:

The VGG19 model is designed for image classification tasks and has been widely used in computer vision applications.

It is characterized by its simplicity and uniformity, with a stack of convolutional layers followed by max-pooling layers.

Architecture:

The VGG19 model consists of 19 layers, including 16 convolutional layers and 3 fully connected layers.

Each convolutional block comprises multiple convolutional layers (with 3x3 filters) followed by a max-pooling layer.

The fully connected layers at the end of the network serve as the classification head, producing the final output predictions.

The model architecture is relatively deep compared to previous models at the time of its introduction, contributing to its effectiveness in learning hierarchical features.

Key Features:

Simple Architecture: The VGG19 model architecture is straightforward and easy to understand, consisting of repeated blocks of convolutional layers.

Weight Sharing: The convolutional layers in VGG19 share weights, allowing the model to learn spatial hierarchies of features effectively.

Transfer Learning: Pre-trained versions of the VGG19 model on large-scale datasets like ImageNet are commonly used as feature extractors or fine-tuned for specific tasks due to their effectiveness in capturing generic image features.

Applications:

Image Classification: The primary application of the VGG19 model is image classification, where it predicts the class labels of input images.

Feature Extraction: The pre-trained VGG19 model can be used to extract high-level features from images, which can then be fed into another model for tasks like object detection or segmentation.

Transfer Learning: Researchers and practitioners often leverage pre-trained VGG19 models for transfer learning on custom datasets, where the model's learned features are adapted to a specific task with limited labeled data.

Performance:

The VGG19 model has demonstrated strong performance on benchmark datasets like ImageNet, achieving competitive accuracy rates in image classification tasks.

However, the model's depth and parameter count make it computationally expensive to train and deploy compared to more modern architectures like ResNet or EfficientNet.

1.3.2 Random Forest Model

The Random Forest model is a popular ensemble learning method used for classification and regression tasks. It operates by constructing a multitude of decision trees during training and outputting the class or mean prediction of the individual trees. Here's a detailed description of the Random Forest model:

Introduction:

Random Forest belongs to the class of ensemble learning techniques, which combine multiple models to improve predictive performance and reduce overfitting.

It was introduced by Leo Breiman and Adele Cutler and is based on the idea of decision tree aggregation.

Architecture:

The Random Forest model consists of a collection of decision trees, where each tree is trained on a random subset of the training data and features.

During training, multiple decision trees are constructed independently, typically using a subset of the available training data and a subset of the available features at each split.

For classification tasks, the final prediction is determined by a majority vote among the individual trees. For regression tasks, it is determined by averaging the predictions of the individual trees.

Key Features:

Ensemble Learning: Random Forest leverages the concept of ensemble learning, combining multiple decision trees to make more accurate predictions than any individual tree.

Feature Randomness: Random Forest introduces randomness both in the selection of training instances (bootstrap sampling) and the selection of features at each node of the decision trees.

Robustness to Overfitting: By aggregating predictions from multiple trees and introducing randomness, Random Forest tends to be less prone to overfitting compared to individual decision trees.

Versatility: Random Forest can be applied to both classification and regression tasks, making it suitable for a wide range of machine learning problems.

Applications:

Classification: Random Forest is commonly used for classification tasks such as image recognition, text classification, and medical diagnosis.

Regression: It can also be applied to regression problems like predicting house prices, stock prices, or customer lifetime value.

Feature Importance: Random Forest can be used to assess the importance of features in a dataset, helping identify the most relevant predictors for a given task.

Performance:

Random Forest typically provides robust performance across various datasets and tasks.

It is less sensitive to noise and outliers compared to some other models, making it a popular choice for real-world applications.

However, the model's interpretability may be limited compared to simpler models like decision trees.

3.1.1 Pseudocode algorithm of proposed model

Step 1:

Dataset preprocessing:

Step 2:

Input images in the VGG19 model for analyses the output of otoscopic media through Deep learning network model.

- ⇨ Model.VGG19() #weight has been used
- ⇨ For each epoch in epoch-number do

For each batch in batch-size do

Input <- image (250, 250,3)

For layer in layers (2) do

Layers_conv(image)

End for loop

Max-pooling (125,125,64) layers

#Changes in filter size to 64 to 128

For layer in layers (2) do

Layers_conv(image)

End for loop

Max-pooling (62,62,128)

#Filter size 128 to 256

For layer in layers (4) do

Layers_conv(image)

End for loop

Max-pooling (31,31,256)

#filter size 256 to 512

For layer in layers (4) do

Layers_conv(image)

End for loop

Max-pooling (15,15,512)

#it might not possible to change the filter size

For layer in layers (4) do

Layers_conv(image)

End for loop

Max-pooling

(15,15,512)Flatten

layers

Dense ()

End for

loop End for

loop

Accuracy ();

Step 3: Best: Accuracy = max (best-Accuracy, Accuracy);

print confusion matrix

Model next step towards the next model through which the tympanometry value has been taken as an input

Step 4:

⇨ **Data set input**

Rn = Random-forest ()

For X-train, Y-test in dataset. Split do

Rn. fit (x-train, y-test)

History <-model. Fit ()

Calculate-performance-matrix (precision, recall, accuracy, f1score, support, Confusion matrix)

Fold

End for

Step 5:

It will be the decision the output from step 4 and step 2 taken through which the major voting will be going on the accuracy will be taken as an output for it. for diagnoses of the patient.

3.1.2 Architectural Diagram of The Proposed Work

MODULE 1: VISUAL GEOMETRY GROUP (VGG-19)

VGG19

The VGG19 model comprises Sixteen convolution layers and three layers thatare completely linked for a total of Nineteen layers. The convolutional layer uses a 3x3kernel with stride 1 and padding 1, whereas the pooling layer uses a 2x2 window withstride 2 for each layer. Each convolutional layer has a constant number of filters, from64 to 512, with a total of 19.6 million parameters, as shown in Fig.5.

Several computer vision tasks, such as image classification, object identification, and picture segmentation, have all been accomplished using the VGG19model. In a number of benchmark datasets, including ImageNet, CIFAR-10, and CIFAR-100, it has demonstrated cutting-edge performance.

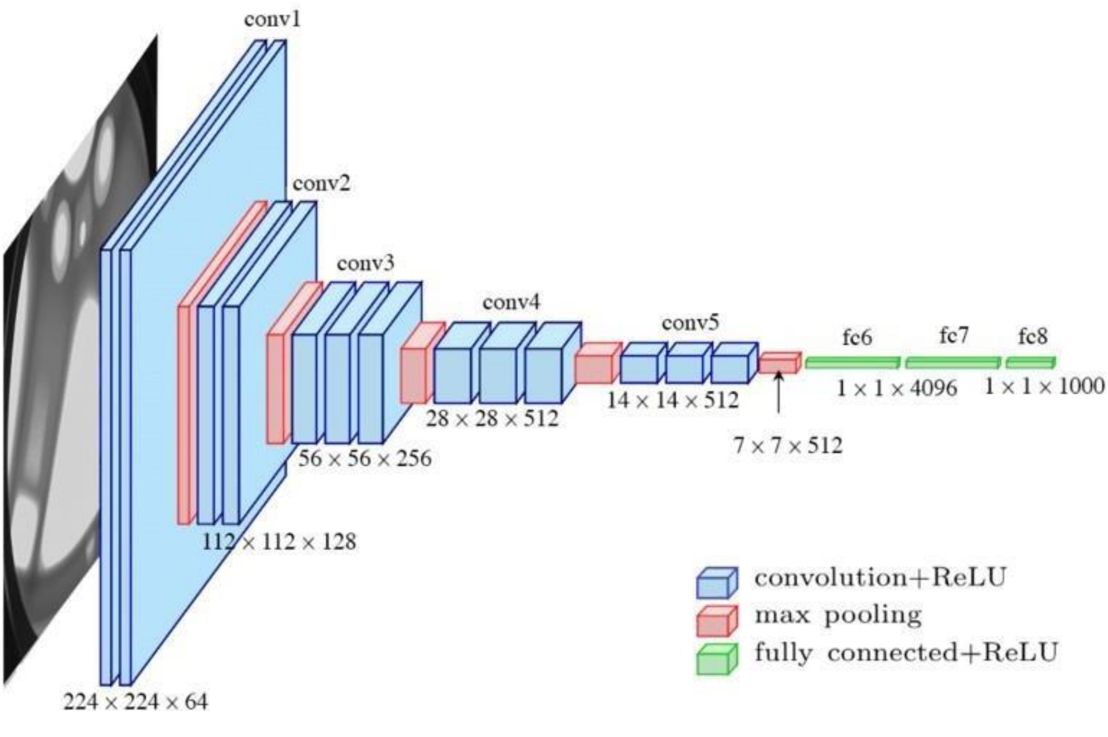


Fig.5. Representation of the VGG-19 architecture used in this research.

Diagram of each class with the class name

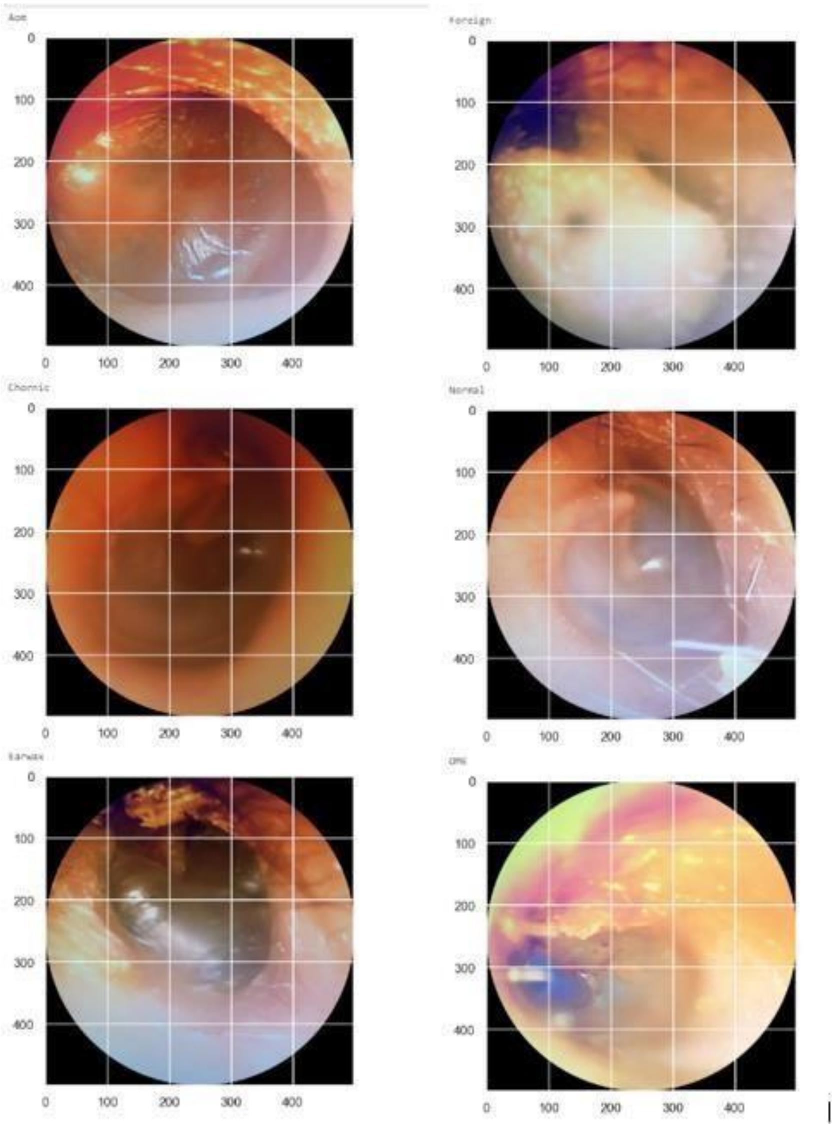


Fig 6. Otoscopic images with there type name

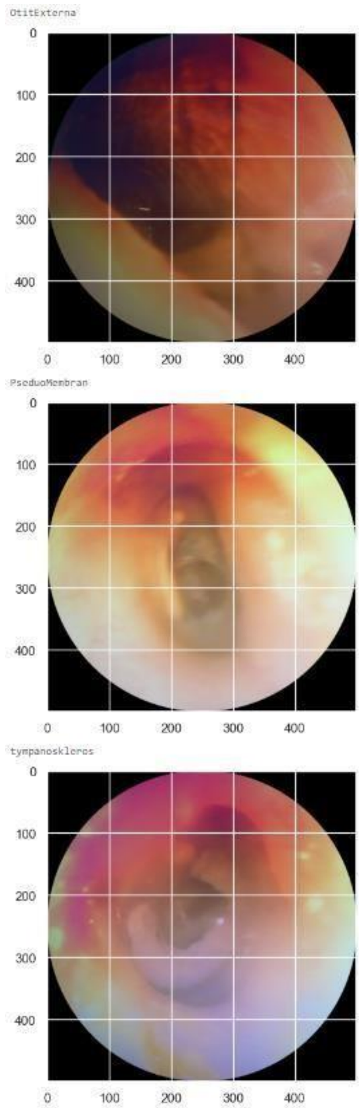


Fig .7 Otoscopic images with there class name.

3.1 Converting images to pixel

In the VGG19 model, images are converted into pixel values in order to transform them into numerical data that can be processed by the model. This is a fundamental step because Convolutional Neural Network (CNN) models like VGG19 are designed to learn from large datasets of images to identify and recognize patterns and features in the images. To accomplish this, the model partitions the image into a matrix of individual pixels, each assigned a numerical value representing the color intensity or brightness of that point. These pixel values then serve as input data for the model during training.

By using pixel values as input data, the VGG19 model can develop its ability to recognize features in the images, such as edges, shapes, and textures. The model can then leverage this knowledge to make predictions about new images it encounters. Additionally, the model can learn to identify groups of pixels that correspond to specific objects or features in the image, allowing it to make accurate predictions .

Algorithm

Step 1:

The size of the image (255*255) was set as input for the model .

Model <- Sequential ()

Step 2:

For each input image, the preprocessing of the RGB value is performed. Freeze the weights of the pre-trained layers

For layers in VGG19_layer do

Model <- layer

End for

Step 3:

To ensure that the entire image is covered, kernels with a size of (3 * 3) and a step length of 1 pixel were used. Specifically, the kernel size of (3*3) with a step length of 1 pixel was used.

Step 4:

Spatial Padding was used to get the spatial resolution of the image.

Step 5:

Max pooling was performed using a 2*2-pixel frame with a stride length of 2.

Step 6:

To improve classification accuracy and computation time, RELU was added to introduce nonlinearity into the model.

Step 7:

The model contained three fully connected layers. The first two layers had asize of 4096, while the third layer consisted of a SoftMax function.

⇨ Model <- Dense (128)

⇨ Model <- Dense (256)

⇨ Model <- Dense (512)

MODULE 2 : RONDOM FOREST MODEL

Random forest using of Tympanometry:

Architecture of Random Forest: The tympanometry data was collected from the clinical guide and the peak values of the tympanogram were used to train the random forest classifier.[20]

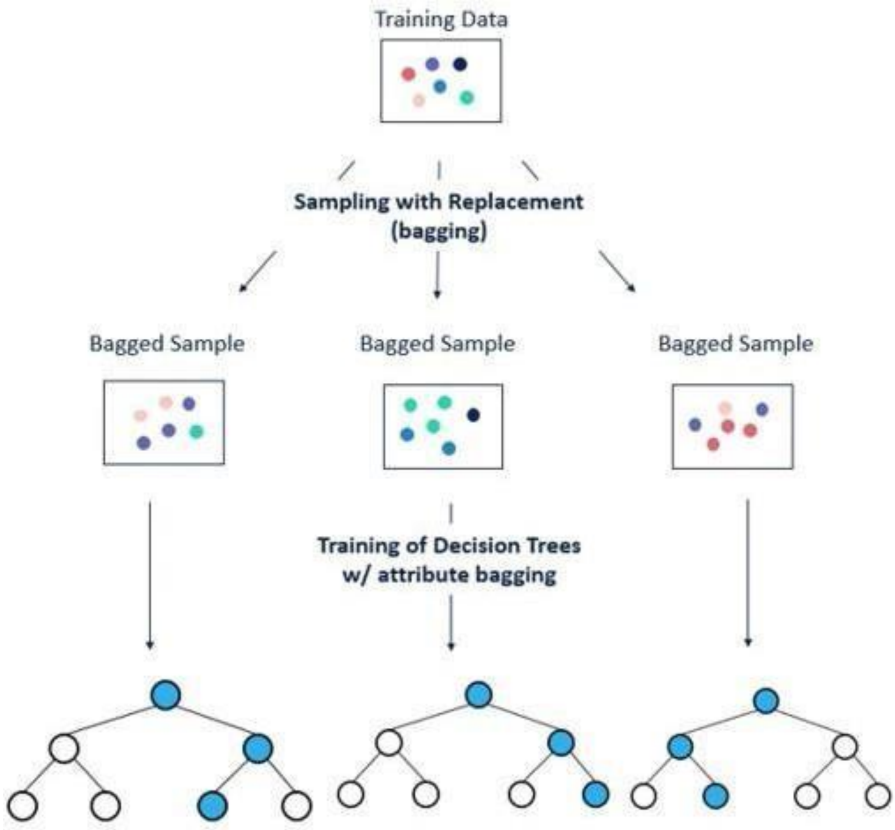


Fig.8. random forest

3.2 DATASET :

The dataset used in this study was collected and it was preprocessed by selecting the peak value of the tympanogram for each recording. This approach was chosen as it hasbeen shown to be effective for typanogram classification using random forest classifiermodels. The final dataset consisted of recordings, with two features extracted from each recording.below is the each patient records diagram with each class.

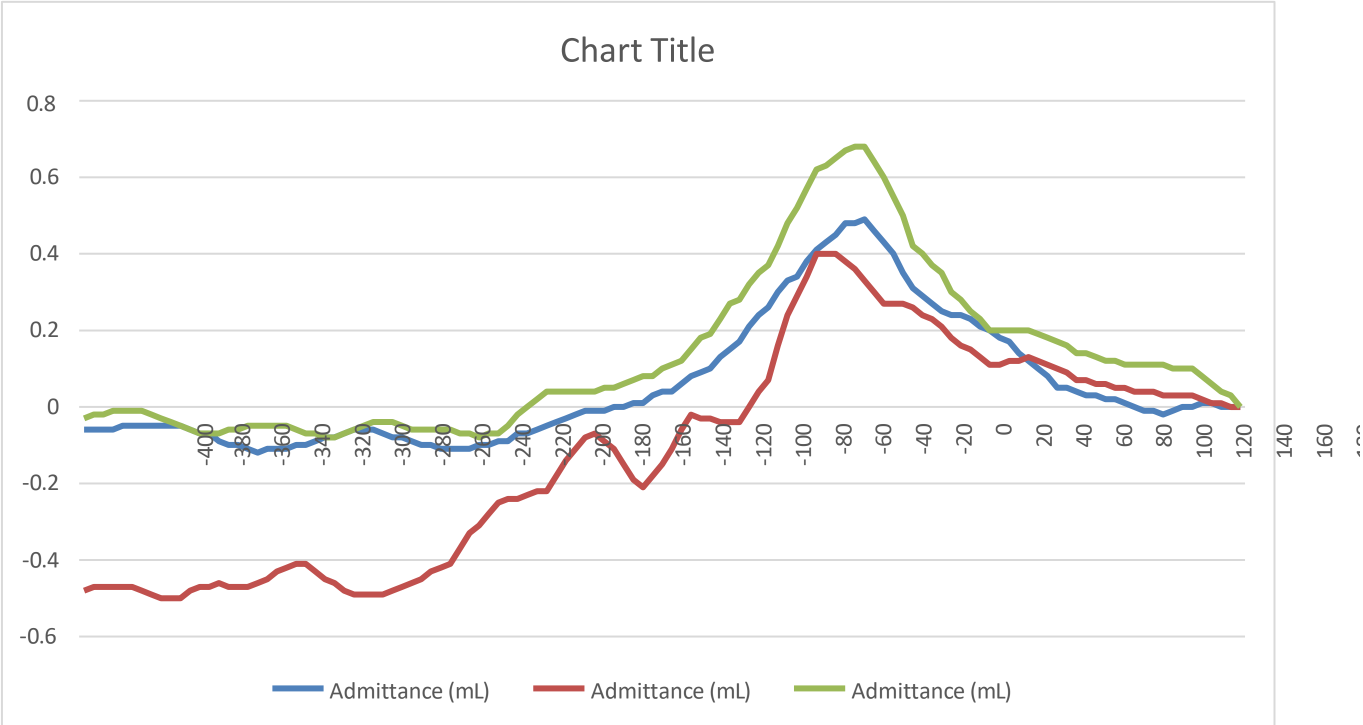


Fig 9 Tymponogram

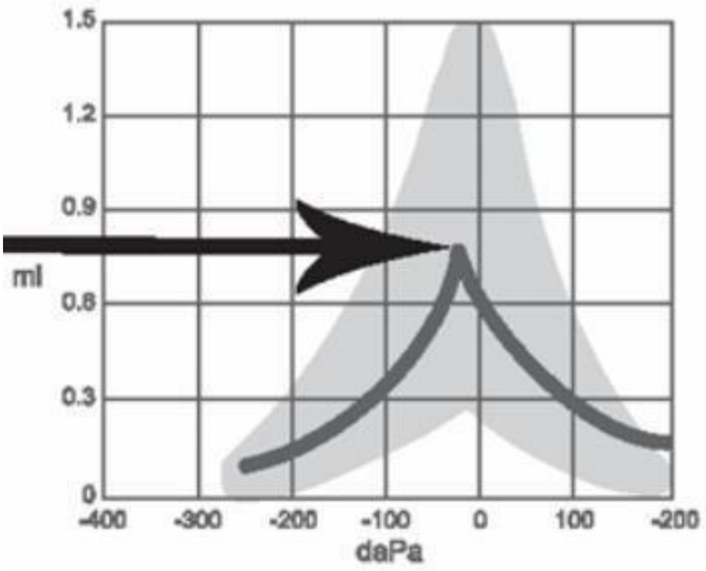


Fig 10 Different class peak value

Tympanometry is a test that measures the movement of the eardrum in responseto changes in air pressure. There are different types of tympanometry curves that can indicate different ear conditions:

Normal ME Curve: This curve indicates normal ME pressure and normal MEcompliance, indicating proper functioning of the eardrum and ossicles.

Ad Curve: This curve indicates an ossicular discontinuity, which means there isa break or separation in one of the ossicles. The MEpressure is normal, but the compliance is decreased due to the broken ossicle's inability to vibrate effectively.

As Curve: This curve indicates otosclerosis, which is a condition where the ossicles become abnormally rigid and cannot vibrate properly. The ME pressure is normal, but the compliance is decreased due to the stiffness of the ossicles.

B Curve: This curve indicates serous otitis media, a type of ear infection wherefluid accumulates in the middle ear. The ME pressure is negative (lower than atmospheric pressure), and the compliance is decreased due to the presence of fluid inthe middle ear. The curve is dome-shaped and can become flat if the fluid does not move and the eardrum cannot vibrate.

C Curve: This curve indicates an early stage of eustachian tube obstruction, which means that the eustachian tube (the tube that connects the MEto the back of the throat) is not functioning correctly. The MEpressure is negative, but the compliance isnormal because the eardrum can still move despite the negative pressure.

Module -3 : Fusion

Fusion methodology:

The classifiers are set up in parallel, execute classification simultaneously, andthen their findings to make a judgement. displays the decision fusion in parallel.

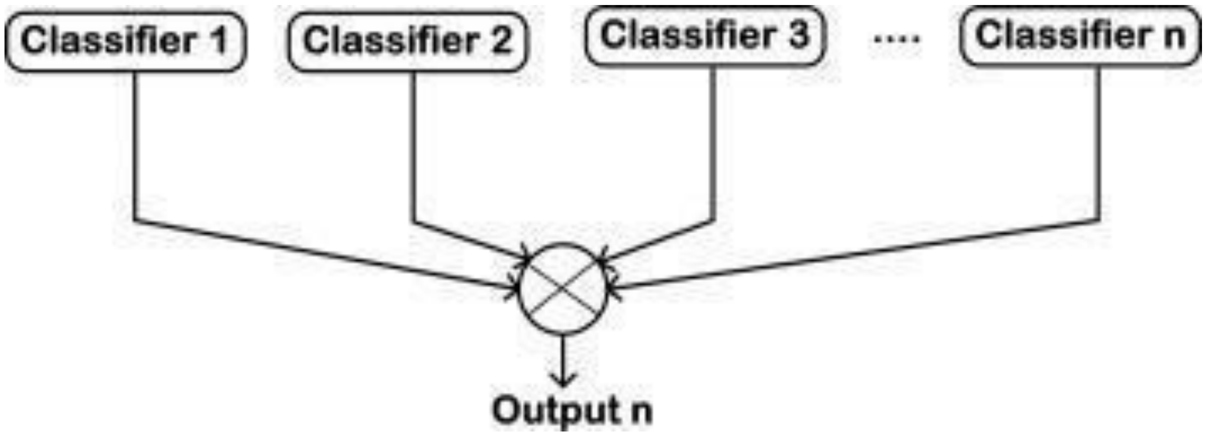


Fig.11 FUSION METHOLOGY

4.1 RESULTS AND DISCUSSION

The proposed model that we developed in this study showed a remarkable accuracy of 93.3% in predicting the outcome, which indicates its potential to effectively diagnose ear-drum infection using otoscopic image analysis andtympanometry. However, when compared to the base model, the suggested model's accuracy fell short. The superior performance of the base model may be attributed to its simpler architecture and lower complexity, which made it more effective indetecting the presence of ear-drum infection. Despite the suggested model's inferior accuracy, it is still a promising tool in diagnosing ear-drum infection, especially whencoupled with other diagnostic methods.

To further evaluate the performance of our model, we generated a confusion matrix using the projected and actual result data, as shown in Fig. 8. The matrix showsthat the suggested model has a high true positive rate, indicating that it can detect ear-drum infection with a high level of accuracy. However, it also has a relatively high false positive rate, which suggests that caution should be exercised in interpreting themodel's results. Overall, our study provides valuable insights into the potential of decision fusion on otoscopic image analysis and tympanometry in diagnosing ear- drum infection, although further research is needed to optimize the model's accuracy and reliability.

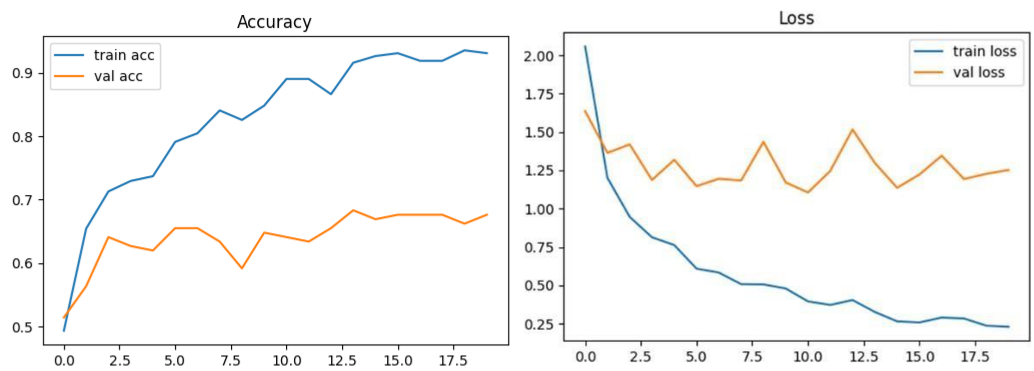


Fig.13. Accuracy epoch vs loss epoch graph

Fig.13. compares loss and epoch accuracy in relation to the graphical representation ofeach module. Even our proposed approach, which has more accuracy than employing two models, has lower accuracy than the current model.

Table 1 . Comparison of the existing and proposed work accuracy result

Metric	Existing model (Tympanometry WBT)	Proposed model (Fusion of two model VGG19 and Random Forest Model.	Proposed model (Random Forest model in which the only tympanogram values used)
Accuracy	92.6	93.5	92.
Sensitivity	92.6	96	96.3
Specificity	92.6	89	83.3

5.1 CONCLUSION & FUTURE WORK

An otoscopic tool is used by experts, but even its use has caused many errors in human eyesight. However, using this tool can help indicate ME drum activity, but it has limitations in viewing. On the other hand, tympanometry can easily define the movement of the inner ear drum, and each method has different sources of output.whileotoscopic and tympanometry methods have their limitations, combining these two methods can provide more accurate and comprehensive diagnostic data for ear infections. Our model that combines tympanometry and otoscopic image processing can be especially useful in areas where ENT experts and specialized diagnostic tools are not readily available. By precisely identifying the type of ear infection a patient has, medical professionals can administer the most suitable medication promptly, improvingpatient outcomes and reducing the risk of complications.

Despite achieving a high accuracy, there is still room for improvement in the suggested model's performance. Future research could focus on refining the features used in the otoscopic image analysis and tympanometry to enhance the model's ability to detect middle ear infections accurately. Additionally, incorporating other diagnostic tools or medical history data could potentially improve the accuracy of the decision fusion approach. Overall, the results suggest that decision fusion has potential as a valuable tool in the diagnosis of middle ear infections.

To further improve the accuracy and effectiveness of our combined model, collecting more data and feedback from medical professionals can be valuable. Additionally, implementing telemedicine technologies could enhance the accessibility and convenience of our model for patients in remote areas. With telemedicine, medical professionals can remotely diagnose and treat ear infections using the combined model,eliminating the need for patients to physically visit a clinic.

Another potential future enhancement is the incorporation of artificial intelligence (AI) or machine learning algorithms into the combined model. AI and machine learning algorithms can potentially improve the accuracy and speed of diagnosing ear infectionsby analyzing large amounts of data and identifying patterns and trends.

Overall, our model that combines tympanometry and otoscopic image processing has the potential to significantly improve the accuracy and timeliness of diagnosing ear infections, making healthcare more accessible and efficient for patients in both urban and remote areas.

Appendix 1

1.1 ALGORITHEM CODE

MODULE 1 : VISUAL GEOMETRY GROUP (VGG-19)

Importing libraries

```
import os

import cv2

import pickle

import numpy as np

import pandas as pd

import seaborn as sns

import matplotlib.pyplot as plt

import matplotlib.image as mpimg


import keras

import tensorflow


from tensorflow.keras.models import Model

from tensorflow.keras.utils import plot_model

from tensorflow.keras.models import Sequential

from tensorflow.keras.applications import VGG19
```

```
from tensorflow.keras.callbacks import
EarlyStopping

from tensorflow.keras.preprocessing.image import
ImageDataGenerator

from tensorflow.keras.layers import Input,
Lambda, Dense, Flatten, Dropout,
BatchNormalization, Activation


from sklearn.metrics import confusion_matrix,
classification_report, accuracy_score,
recall_score, precision_score, f1_score
```

Defining data paths

```
train_path = 'C:/Users/Nabil Ashraf/Desktop/ear
drum/train_data'

test_path = 'C:/Users/ Nabil Ashraf/Desktop/ear
drum/test_data'

val_path = 'C:/Users/ Nabil Ashraf/Desktop/ear
drum/vali_dat
```

Converting image to pixels

```
size = (250, 250)
for folder in os.listdir(train_path):
```

```
    sub_path = train_path + "/" + folder
    print(folder)
    temp_path = os.listdir(sub_path)[1]
    temp_path = sub_path + "/" + temp_path
    img = mpimg.imread(temp_path)
    imgplot = plt.imshow(img)
    plt.show()

def imagearray(path, size):
    data = []
    for folder in os.listdir(path):
        sub_path=path+"/"+folder

        for img in os.listdir(sub_path):
            image_path=sub_path+"/"+img
            img_arr=cv2.imread(image_path)
            img_arr=cv2.resize(img_arr, size)
            data.append(img_arr)

    return data
size = (250,250)

train = imagearray(train_path, size)
test = imagearray(test_path, size)
val = imagearray(val_path, size)
```

Normalization

import numpy as np from keras.preprocessing.image import ImageDataGenerator

```
x_train = np.array(train)
x_test = np.array(test)
x_val = np.array(val)

x_train = x_train/255.0
x_test = x_test/255.0
x_val = x_val/255.0
```

Define target variables

```
def data_class(data_path,  size,  class_mode):
    datagen = ImageDataGenerator(rescale = 1./255)
    classes = datagen.flow_from_directory(data_path,
                                          target_size = size,
                                          batch_size = 32,
                                     class_mode = class_mode)
    return classes
```

VGG19 Model

```
vgg = VGG19(input_shape = (250, 250, 3), weights =
'imagenet', include_top = False)
for layer in vgg.layers:
    layer.trainable = False

x = Flatten()(vgg.output)
prediction = Dense(9, activation='softmax')(x)

model = Model(inputs=vgg.input, outputs=prediction)
model.summary()
model.compile(
  loss='sparse_categorical_crossentropy',
```

```
  optimizer="adam",
  metrics=['accuracy']
```

Model Archtecture

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 250, 250, 3)]     0

 block1_conv1 (Conv2D)       (None, 250, 250, 64)      1792

 block1_conv2 (Conv2D)       (None, 250, 250, 64)      36928

 block1_pool (MaxPooling2D)  (None, 125, 125, 64)      0

 block2_conv1 (Conv2D)       (None, 125, 125, 128)     73856

 block2_conv2 (Conv2D)       (None, 125, 125, 128)     147584

 block2_pool (MaxPooling2D)  (None, 62, 62, 128)       0

 block3_conv1 (Conv2D)       (None, 62, 62, 256)       295168

 block3_conv2 (Conv2D)       (None, 62, 62, 256)       590080

 block3_conv3 (Conv2D)       (None, 62, 62, 256)       590080

 block3_conv4 (Conv2D)       (None, 62, 62, 256)       590080

 block3_pool (MaxPooling2D)  (None, 31, 31, 256)       0

 block4_conv1 (Conv2D)       (None, 31, 31, 512)       1180160

 block4_conv2 (Conv2D)       (None, 31, 31, 512)       2359808

 block4_conv3 (Conv2D)       (None, 31, 31, 512)       2359808

 block4_conv4 (Conv2D)       (None, 31, 31, 512)       2359808

 block4_pool (MaxPooling2D)  (None, 15, 15, 512)       0

 block5_conv1 (Conv2D)       (None, 15, 15, 512)       2359808

 block5_conv2 (Conv2D)       (None, 15, 15, 512)       2359808

 block5_conv3 (Conv2D)       (None, 15, 15, 512)       2359808

 block5_conv4 (Conv2D)       (None, 15, 15, 512)       2359808

 block5_pool (MaxPooling2D)  (None, 7, 7, 512)         0

 flatten (Flatten)           (None, 25088)             0

 dense (Dense)               (None, 9)                 225801

=================================================================
Total params: 20,250,185
Trainable params: 225,801
Non-trainable params: 20,024,384
_________________________________________________________________
```

Fig .13 VGG19 ARCHTECTURE

```
Early_stop = EarlyStopping(monitor = 'val_loss',
mode='min', verbose = 1, patience = 10)

VGG = model.fit(x_train, y_train, validation_data
=(x_val,y_val), epochs =
20,callbacks=[Early_stop],batch_size = 30)
```

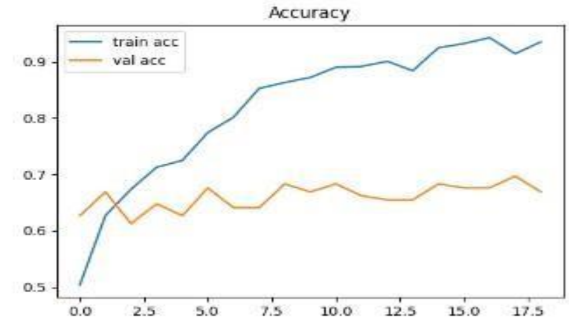
```
In [16]: VGG = model.fit(x_train, y_train, validation_data =(x_val,y_val), epochs = 20,callbacks=[early_stop],batch_size = 30)

Epoch 14/20
23/23 [==============================] - 344s 15s/step - loss: 0.3698 - accuracy: 0.8842 - val_loss: 1.1117 - val_accuracy:
0.6549
Epoch 15/20
23/23 [==============================] - 346s 15s/step - loss: 0.2843 - accuracy: 0.9248 - val_loss: 1.1156 - val_accuracy:
0.6831
Epoch 16/20
23/23 [==============================] - 346s 15s/step - loss: 0.2641 - accuracy: 0.9323 - val_loss: 1.0920 - val_accuracy:
0.6761
Epoch 17/20
23/23 [==============================] - 342s 15s/step - loss: 0.2429 - accuracy: 0.9429 - val_loss: 1.0794 - val_accuracy:
0.6761
Epoch 18/20
23/23 [==============================] - 340s 15s/step - loss: 0.2887 - accuracy: 0.9143 - val_loss: 1.1129 - val_accuracy:
0.6972
Epoch 19/20
23/23 [==============================] - 343s 15s/step - loss: 0.2496 - accuracy: 0.9353 - val_loss: 1.1708 - val_accuracy:
0.6690
Epoch 19: early stopping
```

Fig. 14 EXCUTION OF MODEL

Visualization

```
In [17]: plt.figure(figsize=(6, 4))
         plt.plot(VGG.history['accuracy'], label='train acc')
         plt.plot(VGG.history['val_accuracy'], label='val acc')
         plt.legend()
         plt.title('Accuracy')
         plt.show()
```




```
In [18]: plt.figure(figsize=(6, 4))
         plt.plot(VGG.history['loss'], label='train loss')
         plt.plot(VGG.history['val_loss'], label='val loss')
         plt.legend()
         plt.title('Loss')
         plt.show()
```

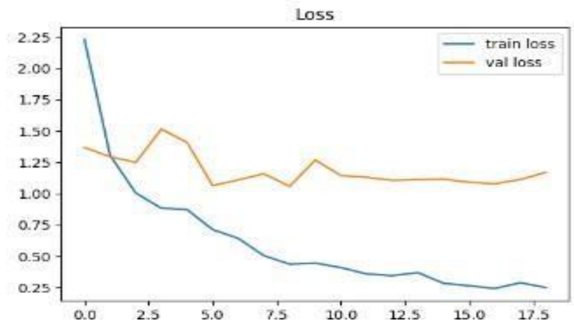


Fig. 15 VISUALIZATION CHART

Model Evaluation

```
In [60]: model.evaluate(x_test, y_test, batch_size=32)

18/18 [==============================] - 417s 23s/step - loss: 0.2889 - accuracy: 0.9460

Out[60]: [0.28891775012016296, 0.9459930062294006]
```

```
In [61]: y_pred = model.predict(x_test)

18/18 [==============================] - 415s 23s/step
```

```
In [62]: y_pred=np.argmax(y_pred,axis=1)
```

```
In [63]: print(confusion_matrix(y_test,y_pred))
         print('\n')

[[ 21   0   1   0   2   0   0   0   0]
 [  3  12   0   0   0   0   0   0   0]
 [  1   0  66   0   3   0   0   0   0]
 [  0   0   0   2   0   0   0   0   0]
 [ 16   1   0   0 392   0   0   1   1]
 [  0   0   0   0   0   5   0   0   0]
 [  1   0   0   0   1   0  25   0   0]
 [  0   0   0   0   0   0   0   5   0]
 [  0   0   0   0   0   0   0   0  15]]
```

```
In [64]: print('Accuracy : %.3f' %accuracy_score(y_test,y_pred))

         result1 = round((accuracy_score(y_test,y_pred)),3)
         result1

Accuracy : 0.946

Out[64]: 0.946
```

```
In [65]: print(classification_report(y_pred,y_test))

              precision    recall  f1-score   support

           0       0.88      0.50      0.64        42
           1       0.80      0.92      0.86        13
           2       0.94      0.99      0.96        67
           3       1.00      1.00      1.00         2
           4       0.95      0.98      0.97       398
           5       1.00      1.00      1.00         5
           6       0.93      1.00      0.96        25
           7       1.00      0.83      0.91         6
           8       1.00      0.94      0.97        16

    accuracy                           0.95       574
   macro avg       0.94      0.91      0.92       574
weighted avg       0.94      0.95      0.94       574
```

Fig .16. MODEL EVALTION

Confusion Matrix

```
conf_mat = confusion_matrix(y_pred, y_test)
plt.figure(figsize=(8, 6))
ax = plt.subplot()
sns.set(font_scale=1.0)
sns.heatmap(conf_mat, annot=True, fmt='g',
cmap="Blues", ax=ax)
```

```
# labels, title and ticks
ax.set_xlabel('Predicted labels', fontsize=10)
ax.set_ylabel('True labels', fontsize=10)
ax.set_title('Confusion Matrix', fontsize=10)
ax.xaxis.set_ticklabels(['AOM', 'Chronic',
'Earwax', 'Foreign', 'Normal', 'OME', 'Otitis
Externa', 'PseudoMembrane', 'Tympanosclerosis'],
fontsize=8)
ax.yaxis.set_ticklabels(['AOM', 'Chronic',
'Earwax', 'Foreign', 'Normal', 'OME', 'Otitis
Externa', 'PseudoMembrane', 'Tympanosclerosis'],
fontsize=8)
```

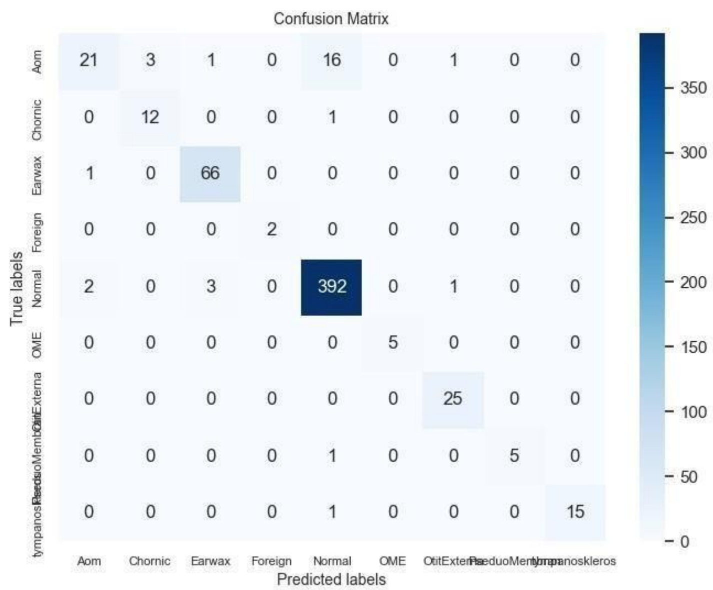


Fig. 17 CONFUSION MATRIX

```
model.save("modelVGG19.h5")
```

MODULE 2 : RONDOM FOREST MODEL

Random forest Model

```
# This just for the One type of Diagnose i have colleted
the Data for it .
```

```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
```

importing the dataset

```
df= pd.read_csv('C:/Users/MD AYAN
ZAFAR/Documents/capstone
project/dataset/Book.csv')

X= df.drop(columns=['classification'], axis=1)
y= df['classification']
```

splitting the data

```
X_train, X_test, y_train, y_test =
train_test_split(X, y,test_size=0.2,
random_state=1)
```

Random forest Model

```
rf=
RandomForestClassifier(criterion='gini',n_estimat
ors=30,random_state=25,n_jobs=5)

rf.fit(X_train,y_train)


prediction= rf.predict(X_test)
print('Accuracy : %.3f'
%accuracy_score(y_test,prediction))
result2 =
round(accuracy_score(y_test,predicti
on),3) result2

Accuracy : 0.917

0.917
```

```
print(confusion_matrix(y_test,p
rediction))print('\n')

print(classification_report(y_test,prediction))
```

Output of the model :

```
In [77]: print(confusion_matrix(y_test,prediction))
         print('\n')

[[8 0 1]
 [0 2 0]
 [0 0 1]]


In [78]: print(classification_report(y_test,prediction))
              precision    recall  f1-score   support

           A       1.00      0.89      0.94         9
           B       1.00      1.00      1.00         2
           C       0.50      1.00      0.67         1

    accuracy                           0.92        12
   macro avg       0.83      0.96      0.87        12
weighted avg       0.96      0.92      0.93        12
```

Fig 18 CLASSIFICSION REPORT

Module -3 : Fusion

Fusion methodology

```
def
simple_average(
results): n =
len(results)
fused_result = sum(results) / n
return fused_result

results =
[result1,result2]
fused_result =
simple_average(results)
print(fused_result)

0.933
```

Appendix 2

2.1 RELATED WORK

Deep learning has emerged as a branch of machine learning that has gained significant attention in recent years. It is a data processing method that utilizes multiple layers of complex structures or processing layers comprised of multiple nonlinear transformations. Deep learning has made breakthroughs in computer vision, speech recognition, natural language processing, audio recognition, and bioinformatics, making it one of the top technological breakthroughs . The method simulates the human neural network, abstracting the original data layer by layer and obtaining different levels of abstract features that can be used for target detection, classification, or segmentation. One of the advantages of deep learning is its ability to replace manual feature acquisition with unsupervised or semi-supervised feature learning and hierarchical feature extraction efficient algorithms.

The medical industry generates a vast amount of data, and making good use of this data can contribute to the advancement of medical care. However, there are several challenges when dealing with medical data, such as its diverse formats, including maps, texts, videos, and magnets, and the varying quality of data due to the use of different equipment. Data can also present fluctuating characteristics over time and in response to specific events, and the law of the disease has no universal applicability due to individual differences. Medical imaging is a crucial part of medical data and plays an important role in diagnosis and treatment.

Otitis media (OM) is one of the most common pediatric illnesses worldwide, characterized by inflammation and/or infection of the middle ear. One of the diagnostic methods to confirm the presence of OM is otoscopy, where a physician examines the ear canal and tympanic membrane (eardrum) using an otoscope. However, the interpretation of otoscopic images can be subjective and may lead to inconsistent diagnoses, especially in the case of inexperienced examiners. Tympanometry is another diagnostic tool used to evaluate middle ear function and detect the presence of fluid behind the eardrum. Despite its high sensitivity, tympanometry alone may not always provide a definitive diagnosis of OM.

To address the limitations of each method, the combination of otoscopy and tympanometry has been suggested as a promising approach to improve the accuracy ofOM diagnosis. Decision fusion is a technique that allows the combination of information from multiple sources to make a more accurate diagnosis than using eithersource alone. In this context, decision fusion of otoscopy and tympanometry could leadto a more accurate and reliable diagnosis of OM, especially in cases where one methodalone may not be sufficient.

Ear infections, also known as otitis media, are a common health problem, especially in children. According to the Centers for Disease Control and Prevention (CDC), around 5 out of 6 children experience at least one ear infection by the time theyreach three years of age. Otitis media occurs when fluid builds up in the middle ear, causing inflammation and infection. The condition is often accompanied by symptomssuch as ear pain, fever, and hearing loss.

Diagnosing ear infections can be challenging, as the symptoms can be similar to other conditions such as allergies or sinus infections. However, early and accurate diagnosis is crucial to ensure proper treatment and prevent potential complications. Traditionally, diagnosis of otitis media has relied on otoscopy, a visual examination ofthe ear canal and eardrum, and tympanometry, a test that measures the movement of the eardrum in response to changes in air pressure.

Recently, there has been growing interest in using machine learning algorithmsto aid in the diagnosis of ear infections. With the advancement of technology, deep learning algorithms have shown great potential in analyzing otoscopic images and accurately detecting middle ear effusions, which are indicative of ear infections.Tympanometry data can also provide valuable information for the diagnosis of ear infections.

Recent advances in machine learning, especially deep learning, have shown promise in improving the accuracy and efficiency of medical image analysis. In this study, we propose a decision fusion model that combines the analysis of otoscopic images using deep learning algorithms with tympanometry data to improve the diagnosis of ear-drum infections. This study aims to investigate the potential of decision fusion in improving the accuracy of OM diagnosis, which could have significant implications for the management of this common childhood illness.

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