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Article Title: Deep Learning Based Ear Disease Prediction a Novel Approach Using Modified Vgg-19 Architecture Enhanching Accuracy

Deep Learning Based Ear Disease Prediction a Novel Approach Using Modified Vgg-19 Architecture Enhanching Accuracy

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ABSTRACT

Middle ear inflammatory diseases are a worldwide health concern that leads to severe effects like speech problems and hearing loss. Experts visually examine the tympanic membrane during a clinical examination. The five classes of Tympanic Membrane (TM) image inside the middle ear is predicted by using the proposed Deep Learning method called Modified VGG-19. Initially, data augmentation is applied to the TM image to eliminate the black margin and to resize, remove noise using bilateral filtering to get high quality input data. Next, the images are segmented using the Fuzzy C-means clustering, allowing for partition of data. Features are then extracted from the segmented images using the Gray-Level Co-occurrence Matrix the TM image is textured for further analysis. Finally, a Modified VGG-19 framework is proposed to enhance the classification of TM images, in middle ear diagnosis. The assessment of proposed work using python software reveals that the proposed framework with Modified VGG-19 classifier ranks with improved accuracy of 92.09 % when compared to the other techniques.

Keywords: Middle ear disease, Data augmentation, Bilateral filter, Fuzzy C-means clustering, Gray-Level Co-occurrence Matrix, Modified VGG-19**.**

1 Introduction

The ear is one of the most important organs in the human body; it is responsible for maintaining body stability in addition to controlling auditory perceptions. Ear infections impact more than 500 million persons annually worldwide, the ear is another organ that is commonly afflicted by diseases. Ear disorders cause lifelong problems and hearing loss if they are not identified and treated quickly [1]. Moreover, they result in serious side effects such acute mastoiditis, labyrinthitis, and meningitis, which significantly lower a person's quality of life for the rest of their life [2].Furthermore, ear infections are among the most prevalent inflammatory illnesses, particularly in youngsters. Almost all kids experience at least one time of ear infections before they turn seven years old. Currently, doctors' standard of care consists on visual inspection and antibiotic prescription [3].Tympanic membrane evaluation is the initial test to diagnose ear disease [4].The latter raises health expenses, delays the appropriate application of treatments, and cause serious problems for the patient. In recent years, new technology to aid in medical diagnosis have emerged as a growing trend

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to lower diagnostic error due to the overview of advanced processing techniques and the large amount of digital data already available [5]. Another technique for locating and identifying anomalies in the inner ear is CT scans [6].

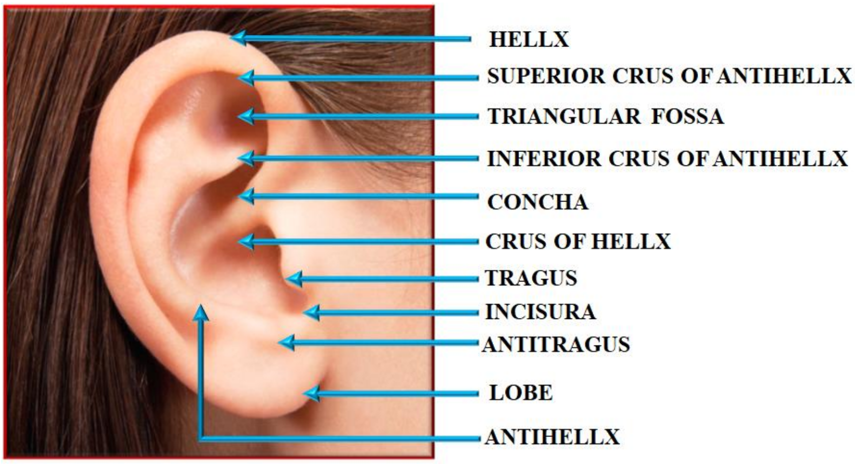

Figure 1: *Structure of human ear*

The exterior and interior parts of the ear structure is illustrated in Figure 1. Important morphological elements such as the lobule, outer helix, anti-helix, tragus, and anti-tragus are found in the exterior shape, whereas the inner structure is made up of many valleys and ridges that combine to form a complex structure with selective potential.

Histogram Equalization (HE) –based Adaptive Center- Weighted Median (ACWM) filter is used to remove the noise and to improve the quality of tympanic membrane image. Drawback is slow in life treating problem [7]. Whereas, using nonlinear filtering the ear infection is identified it is used to enhance the image when removing the noise. When pixel is constant it is crucial to remove noise [8]. To improve the contract of the TM image and for effective detection in the tympanic membrane image Adaptive Histogram equalization (AHE) is used. Drawback is it over amplifies the noise when filtering the tympanic membrane image [9].

The k-means clustering technique is aid to segment and enhance the cluster quality of the middle ear effusion in the tympanic membrane image. TM image is segmented clearly. TM image have inaccurate cluster size when segmenting [10-11]. Image reconstruction is used to segment the raw data into image from inner ear disease. It is a quick process because it does the pre-processing step. Yet is complex to noise for inner ear disease. Whereas, Volumetric Local Thresholding is used to segment the inner ear from patients it have clear images with reduced noise. It is a simple structure, ease of implementation, quick response. Pixel value is distressed when segmenting [13]. For diagnosing middle ear tympanic membrane global-local feature extraction technique is used. It improves the diagnosis structure for TM image. However, it is difficult to successfully balance the diagnosis [14]. Moreover, to visualize the presence of bacteria's on the surface in the middle ear texture feature is used. It improves the

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surface texture to find the bacteria. It is complex to noise [15]. To overcome these problems a deep learning method called Modified VGG-19 is used.

2 Related work

Khan *et al* [16] (2020) have proposed a Convolutional Neural Network (CNN) models, such as DenseNet, to the automated identification of Middle Ear (ME) and Tympanic Membrane (TM) infections. The accurate region for both TM and ME infections using Oto-Endoscopic Images (OEIs), is predicted and increases the accuracy of classification. Each layer's feature maps are joined with the previous layer, and the data is repeated several times. It takes more time when the data is repeated several times.

Başaran *et al* [17] (2020) have proposed a Faster Regional Convolutional Neural Network (Faster R-CNN) designed for tympanic membrane finding in the middle ear. Using VGG-16 model tympanic membrane image improve the diagnostic accuracy and lower the overall misdiagnosis rate. It is over fitting due to its complexity.

Viscaino *et al* [18] (2021) have proposed a Convolutional Neural Network (CNN) -Long Short Term Memory (LSTM) is a conventional diagnostic on optical examination of the tympanic membrane and ear canal. CNN-LSTM is used to identify diagnosis of ear disorders with high performance. This allows a thorough diagnosis of conditions affecting the eardrum and the ear canal. It takes more interval to access the process when diagnosing.

Singh *et al* [19] (2023) have proposed a 2D-CNN model designed for binary and multi-class classification of ear diseases. It maximizes treatment plan, accurate and effective for screening of ear diseases. The prevention of costs depends on the diagnosis of middle ear disorders.

Uçar *et al* [20] (2022) have proposed a Bilateral-Long Short Term Memory **(**Bi-LSTM) network to classify tympanic membrane conditions. It improves the classification accuracy for such classes earwax plug, myringosclerosis, chronic otitis media and normal from the otoscopy images. It necessitates both forward and backward processing of the image data, which take more time for the training period.

The work's contributions include the following:

- Data augmentation is utilized to effectively eliminate black margin from input data and bilateral filter is used to remove unwanted noise from the input TM images, enhancing image quality for diagnosis.
- Fuzzy C-means clustering is employed to segment TM images, fuzzy partition for better feature extraction and diagnosis.
- GLCM to structure and texture the features from the segmented TM images for middle ear for diagnosis.
- A Modified VGG-16 based framework is proposed, to classify the featured TM image from the middle ear for diagnosis.

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3 Proposed work

In the proposed work the five classes of TM images from middle ear is predicted. Firstly, the input data is given to the preprocessing step were an data augmentation technique is applied to eliminate the black margin and by using bilateral filtering the unwanted noise are removed. Secondly, the segmentation process uses the Fuzzy C-means clustering for segmenting TM image. Thirdly, by using GLCM feature extraction technique the segmented TM images are featured by its properties.

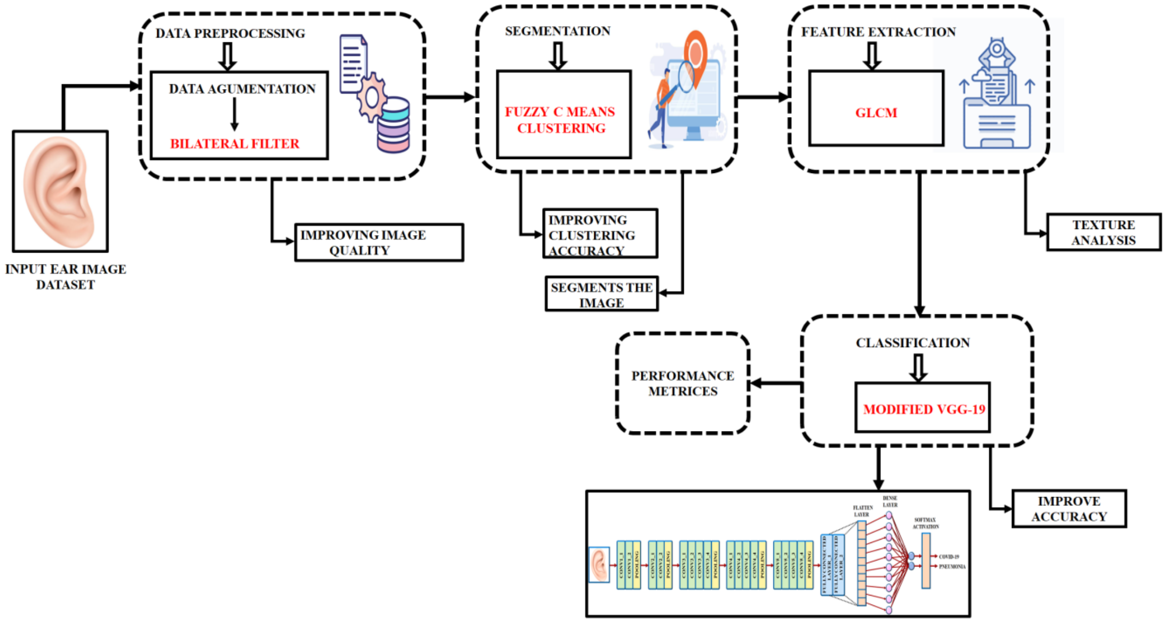

Figure 2: *Block diagram of proposed method*

Finally, featured image is given to the classification process were a proposed Modified VGG-19 is used for classifying the TM image. The Modified VGG-19 have convolutional layers, max polling layer dense layer and softmax layer which is used to classify the TM image in depth for getting better accuracy when compared to the other techniques.

3.1 Pre-processing for TM images

3.1.1 Data argumentation for TM images

An appropriate pre-processing step is required to eliminate the unnecessary black margins from unrefined tympanic membrane images taken from OTOSCOPE dataset. This will increase the speed of inference. Therefore, in order to pre-process the data, first scaled the original image to 270 × 270 resolution and then eliminated the dark margins to resize only the tympanic membrane. The images were then enhanced by casually collecting 256 × 256 areas after the 270 × 270 images and adding random transformations (such as flip, flop, and rotation).

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3.1.2 Bilateral filtering

The bilateral filter is utilized by grayscale conversion; image augmentation and noise reduction were necessary even though preserving image edges and accuracy for TM image. The bilateral filter improves the image's edge pixels by using the grayscale change of the difference between two grayscale pixels and the wave's spatial distance. The following formula provides a definition for it:

$$BF(\mu_p) = \frac{1}{T_p}\sum_{q\in s} H_{\tau d}(\|p-q\|)H_{\tau r}(\mu_p-\mu_q)\mu_q, \tag{1}$$

Some pixel in S is denoted by q, and S is the neighbourhood value centered on p. It is mostly used to quantify the degree of image denoising; $H_{\tau d}$ is a spatial distance function; $H_{\tau r}$reduce the impact of pixels that are located far apart in space. In grayscale, it is comparable. The degree function reduces the impact of certain grayscale levels. The bilateral filter, which is the neutralization function of$H_{\tau d}$, is defined as follows:

$$H_{\tau d} = e^{-(\frac{1}{2})(\frac{d(p,d)}{\tau_d})^2} \tag{2}$$

The Euclidean distance between pixels p and q represented by formula d (p, q). Next, Fuzzy C-Means clustering segmentation for segment TM images.

3.2 Segmentation by Fuzzy C-Means clustering for TM images

A clustering technique called fuzzy C- means (FCM) allows a point to be a member of one or more clusters. The FCM method divides a finite collection of points into a collection of C fuzzy clusters based on principles. As a result, locations near a cluster's margin be more or less part of the cluster than points in the collection's center. The FCM algorithm is derived from the minimization of the following objective function.

$$J_m(\mu, a) = \sum_{i=1}^{c}\sum_{j=1}^{n}\mu_{ij}^{m}(\|x_j - a_i\|)^2, m > 1 \tag{3}$$

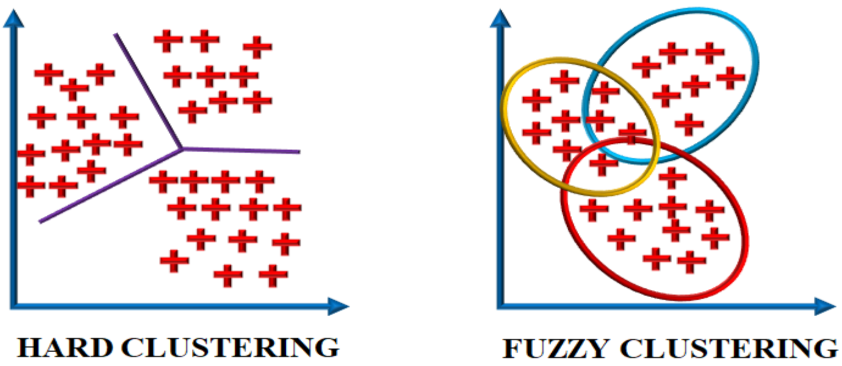

Figure 3: *Fuzzy C-Means clustering*

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Using the fuzzy c-means technique, the TM image is segmented. The FCM algorithm's main parameters are the fuzziness parameter (m) and the number of clusters (k). Fuzzy c-means clustering is the same as k-means clustering if the fuzziness parameter m is equal to 1. Memberships will be allocated to one cluster over the others whenever m is around 1. Next, Feature extraction by GLCM to texture and structure the TM images

3.3 Feature extraction by GLCM for TM images

The Grey-Level Co-occurrence Matrix (GLCM) feature, which uses the distance among two pixels in an image to define its value in the TM images. Whereas a coarse texture region changes more slowly, a fine texture region fluctuations more quickly. In order to extract the texture features, first chose the grayscale image that had additional image information, following their extraction from grayscale images, the texture indices were chosen as texture characteristics based on their strong correlations with ear image. The GLCM intentions in dissimilar window sizes (division: pixel × pixel) were used to quantitatively describe the texture statistical attributes, such as the dissimilarity, entropy, second moment, mean, variance, homogeneity, contrast, and correlation, as well as to quantity the texture thickness, similarity, contrast, uniformity, or regularity of GLCMs in rows or columns.

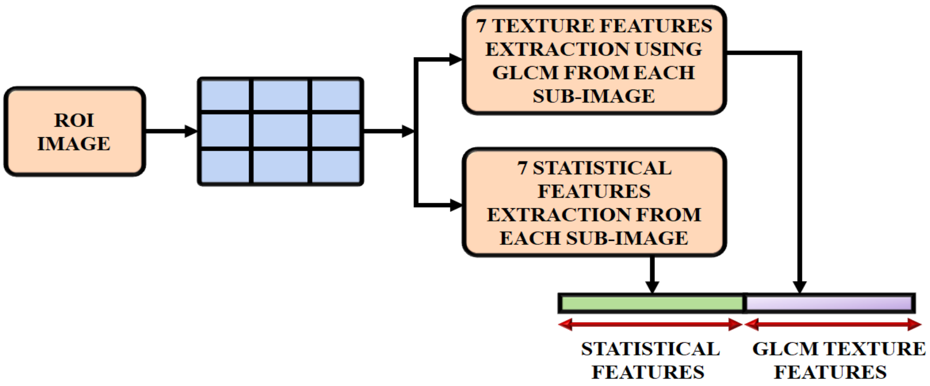

Figure 4: *GLCM features for TM images*

Algorithm of GLCM feature for TM images

1. The first step is to change the color image to grayscale.
2. A 5x5 filter is applied to the input TM image.
3 The filter image is divided into 4x4 pieces.
4. GLCM Characteristics Energy, standard deviation, mean value, homogeneity, and contrast are defined for each block. The computation of these properties is done in four directions: horizontal (90°), vertical (0°), and diagonal (45° and 135°).
5. Features Extracted
Followed by this a featured image is given to the classification step to classify the TM images.

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3.4 Classification by Modified VGG-19 for TM images

The TM image is given to the proposed Modified VGG-19 for diagnosis .Visual Geometry Group Network (VGG Net) is a multi-layered deep neural network. The VGG-19 is nearly simple, with 3 × 3 convolutional layers attached to the top that rise with depth level. In VGG-19, max pooling layers were employed as a handler to decrease the volume size. Here 4096 neurons were employed in two fully connected layers. Each fully connected layer and module are followed by a dropout layer. The max-pool layer serves as the network's dividing line in the VGG-19 network, while the other sixteen layers are divided into five blocks without taking into the fully connected layer. The first two blocks consist of two convolutional layers and one pooling layer, whereas the latter three modules consist of four convolutional layers and one pooling layer.

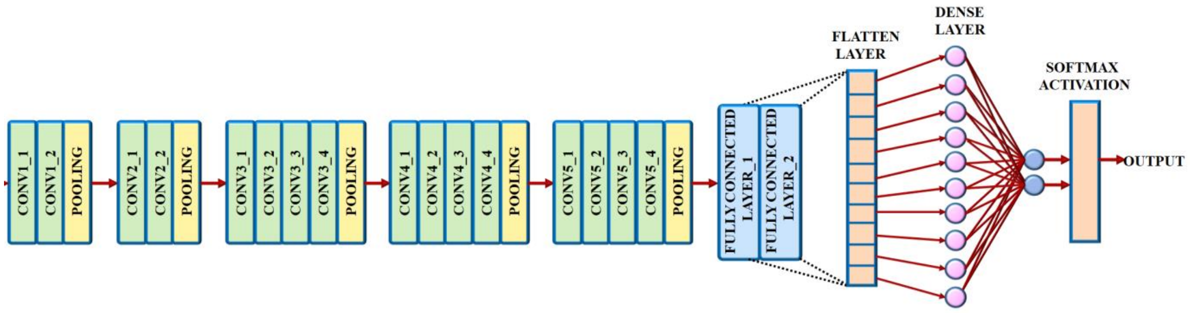

Figure 5: *Modified VGG-19*

During the training phase, convolutional layers were utilized to extract features. To reduce the dimensionality of the features, some convolutional layers were coupled to max pooling layers. In this case, the main convolutional layer used 64 kernels (3 × 3 filter size) to extract features from the input images. Lastly, the TM images were classified using the softmax activation technique during the testing phase using 10-fold cross validation. At last using the proposed Modified VGG-19 the TM is classified.

4 Result and Discussion

4.1 Dataset Collection

A clinical technique called OTOSCOPE is used to look at the ear's structures, namely the middle ear, tympanic membrane, and external auditory canal. The proposed model is analysed on OTOSCOPE data consisting of five classes' aom, csom, earwax, normal, otitisexterna. The dataset is distributed as 80% for training and 20% for testing. Deep learning models are then applied to train on this data.

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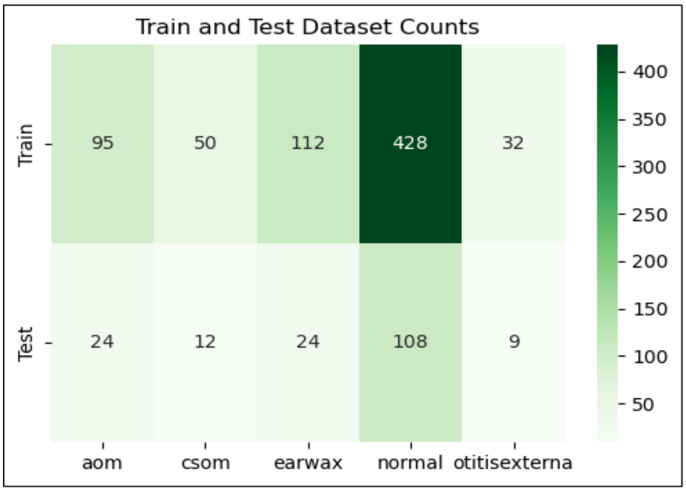

Figure 6: *Train and test dataset counts for TM image*

The figure 6 shows the train and test dataset counts. Here aom is represented by 95 trains and 24 tests; csom is represented by 50 trains and 12 tests; earwax is represented by 112 trains and 24 tests; normal is represented by 428 trains and 108 tests and otitisexterna is represented by 32 trains and 9 tests. These five types of middle ear disease are used in the proposed work.

4.2 Pre-processing by data augmentation

The figure 7 shows the input OTOSCOPE dataset for pre-processing by data augmentation. First the original tympanic membrane image is flipped horizontally and flipped vertically to view the image in both directions then rotated by 45° to brighten and to reduce noise in the original image.

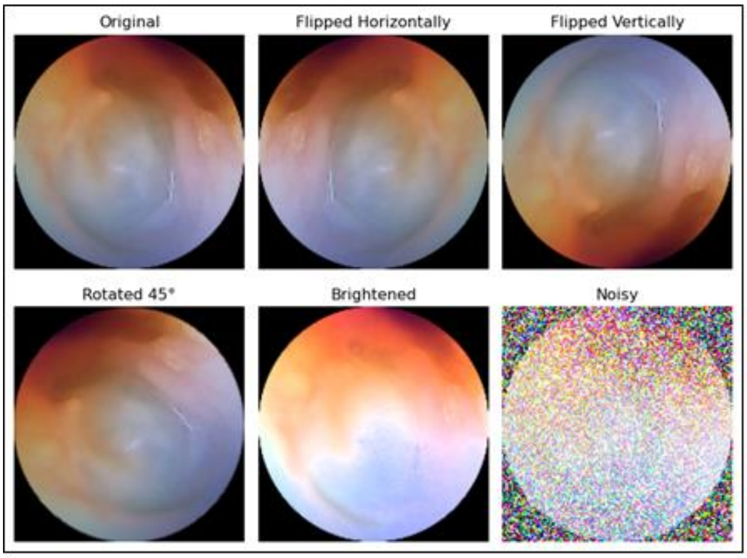

Figure 7: *Data augmentation for TM image*

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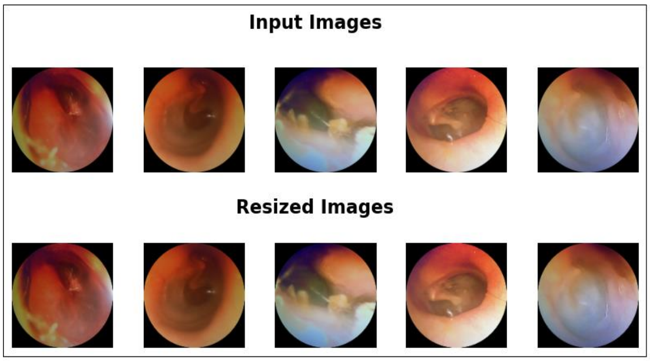
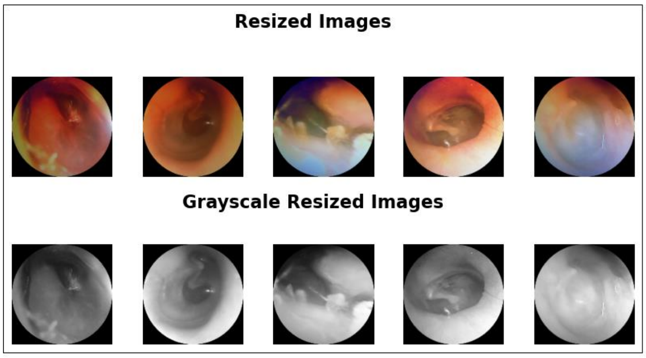
4.3 Bilateral filter

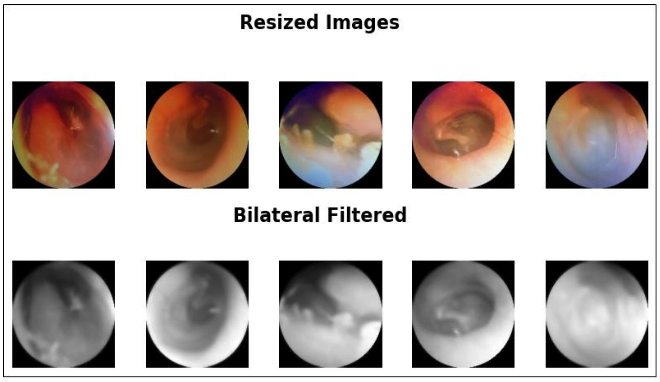
(a)



(b)



(c)



(d)

Figure 8: *(a) Input image from all classes, (b) Resized TM image, (c) Gray scale TM image, (d) Bilateral filtered TM image*

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The figure 8 shows the input image from five classes, resized images, grayscale images and bilateral filtered image. The input image of five classes aom, csom, earwax, normal, otitisexterna each classes is first resized from the input image. Second grey scale conversion occurs for each five classes their color image is changed as grey scale image. Converting images to grayscale preserves important structural details while restructuring image processing. At last using the bilateral filtering the resized images remove the unwanted noise from the grayscale image.

4.4 Fuzzy C-means clustering

The figure 9 shows the Fuzzy-C means clustering applied to TM image. Here the bilateral filter remove unwanted noise and given to the fuzzy-C means clustering to cluster the five classes classes aom, csom, earwax, normal, otitisexterna. It clusters the fuzziness parameter (m) and the number of clusters (k) from the bilateral filtered image.

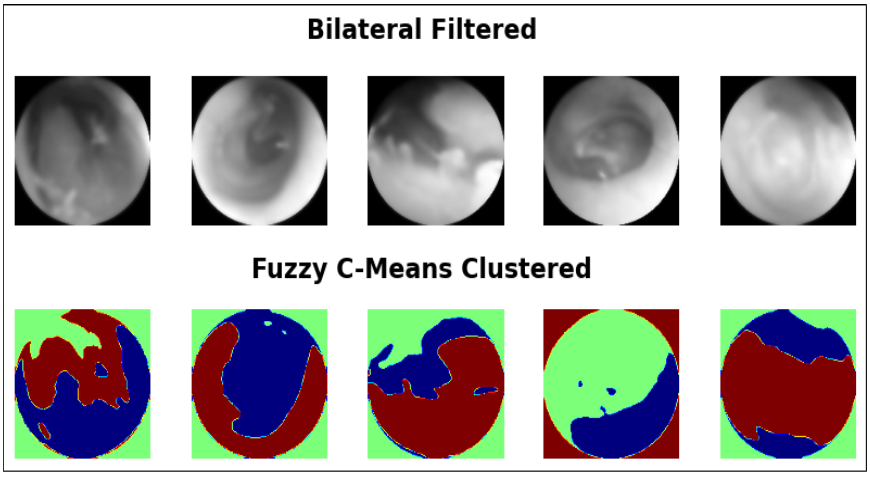

Figure 9: *Fuzzy C-means cluster for TM image*

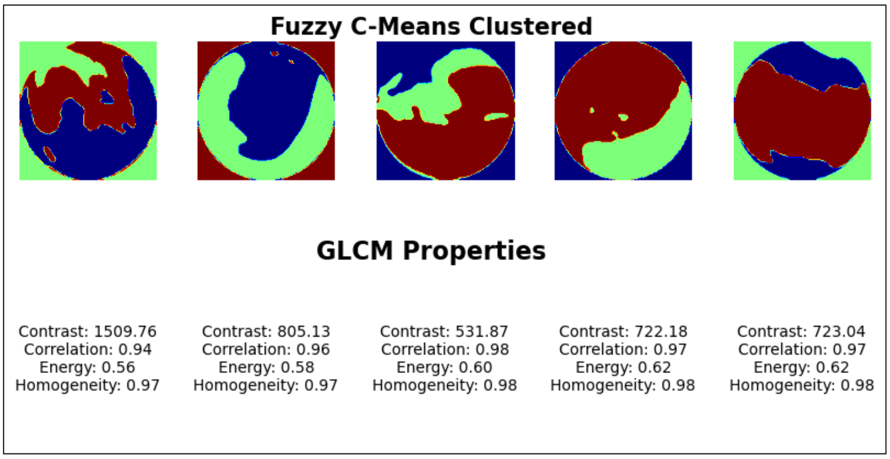

Figure 10: *GLCM properties for TM image*

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The figure 10 shows the GLCM properties for TM image. Here the Gray-Level Co-Occurrence Matrix properties for five classes are calculated from the segmented or clustered image.

Table 1: *GLCM properties*

Classes	Contrast	Correlation	Energy	Homogenity
aom	1509.76	0.94	0.56	0.97
csom	805.13	0.96	0.58	0.97
earwax	531.87	0.98	0.60	0.98
normal	722.18	0.97	0.62	0.98
otitisexterna	723.04	0.97	0.62	0.98

The GLCM features for the five classes are calculated with their properties that are contrast, homogeneity, energy and correlation is in table 1.

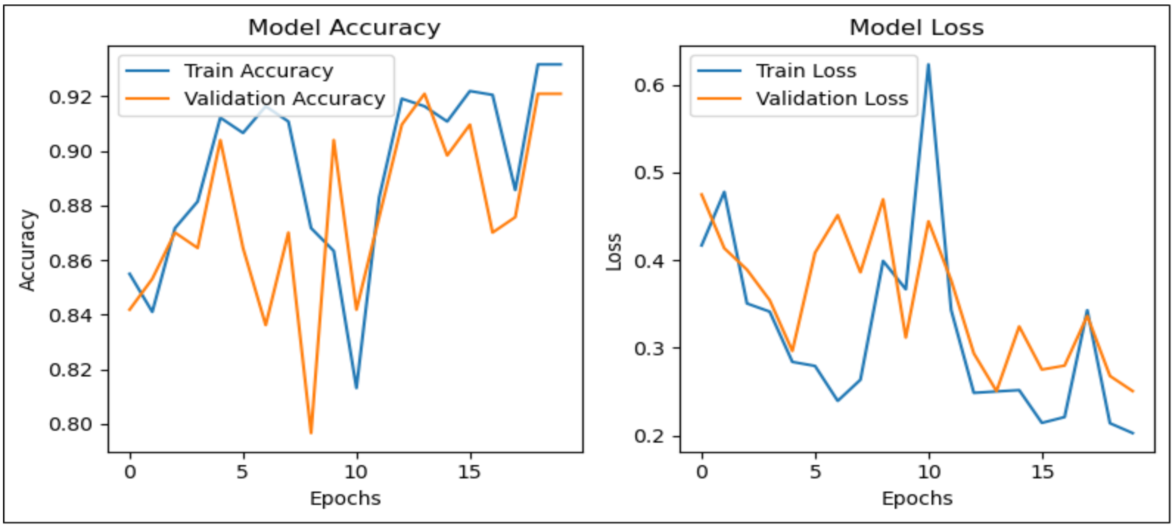

Figure 11: *Model accuracy and model loss for TM image*

The ratio of a model's accurate predictions to its total number of predictions is known as model accuracy. The accuracy for the proposed modified VGG-19 method is 92.09%.The model's loss is demonstrated, which also shows loss value variations and the accuracy of the model is shown graphically in Figure 11.

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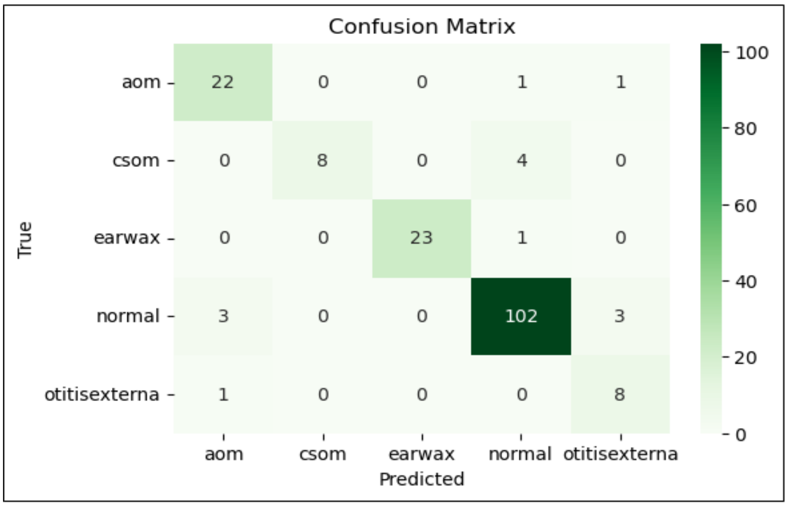

Figure 12: *Confusion matrix for Modified VGG-19*

Figure 12 illustrates the confusion matrix for Modified VGG-19. This matrix shows the values for true and predicted labels. Confusion matrices are commonly used to evaluate the performance of classification models, particularly those tasked with predicting categorical labels for input instances. Here the five classes of TM image for aom, csom, earwax, normal and otitisexterna are matrixes.

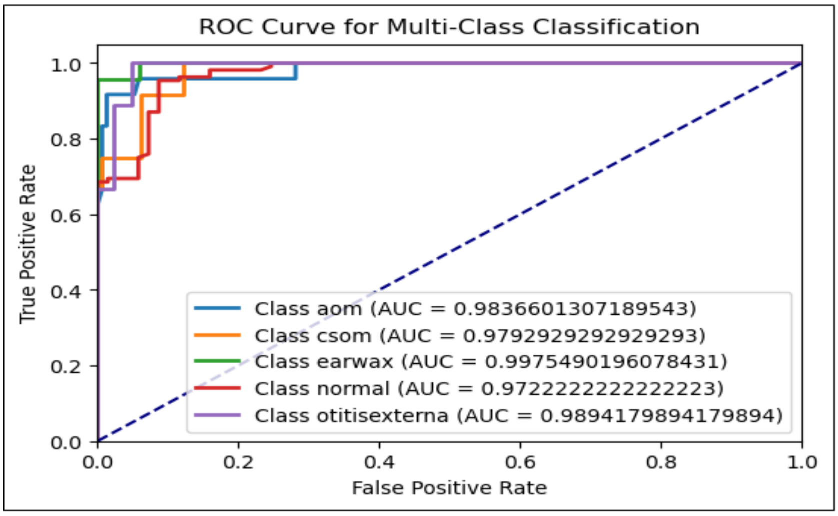

Figure 13: *ROC curve for multi-class classification using modified VGG-19*

According to the AUC results shown in Figure 13, the otoscope dataset significantly lowers the AUC value of modified VGG-19, the sub-optimal model on datasets, to 0.97 for normal TM image, 0.979 for csom, 0.983 for aom and 0.989 for otitisexterna. In comparison, the suggested modified VGG-19 continues to have the highest AUC value of 0.99, demonstrating the exceptional overview and flexibility of this approach.

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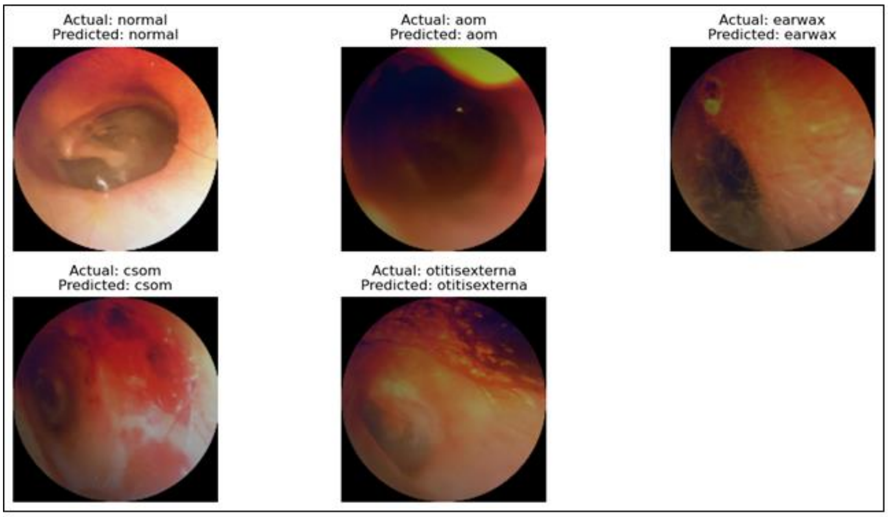

Figure 14: *Predicted image for the five classes using modified VGG-19*

In above figure 14 actual and predicted images are illustrated. For the five classes of tympanic membrane image in the middle ear is predicted successfully. The actual and predicted image for the five classes are normal, csom, aom, otitisexterna, and earwax. The five classes are diagnosed and predicted using Modified VGG-19.

4.5 Performance metrics

Using various performance metrics the suggested method modified VGG-19 outline to training data is evaluated. And these metrics are accuracy, precision, recall, F1 score and AUC. Using the following equation each metrics are defined as

i) Accuracy:

$$\text{Accuracy} = \frac{(\text{TN+TP})}{\text{TS}} \tag{4}$$

ii) Precision:

$$\text{Precision} = \frac{(\text{TP})}{(\text{TP+FP})} \tag{5}$$

iii) Recall:

$$\text{recall} = \frac{(\text{TP})}{(\text{TP+FN})} \tag{6}$$

iv) F1 score:

$$\text{F1} - \text{score} = \frac{(2*\text{Precision}*\text{Recall})}{(\text{Precision} + \text{Recall})} \tag{7}$$

At last, the model's performance across classification thresholds is evaluated using the AUC, which describes the correlation between the true positive and false positive rates for TM image in middle ear.

4.6 Comparison for the proposed method

In contrast with the several other studies [17, 21] depend on baseline data, ignoring the training data's time series component. These studies did not sufficiently explain their findings and lacked training data for disease analysis.

Table 2: *Comparison for the proposed method*

Study	Method	Accuracy
Başaran *et al*. [17]	Faster R-CNN (VGG16)	90.48%
Viscaino *et al*.[21]	CNN	92%
Proposed approach	Modified VGG-19	92.09%

4.7 Comparisons for Modified VGG-19

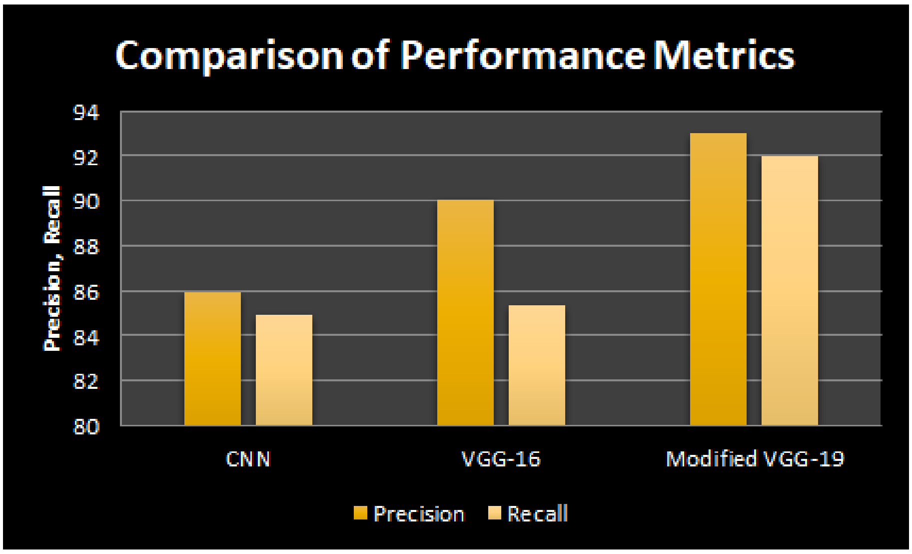

Figure 15: *Comparison of performance metrics*

For Precision and recall it gives better predicted value when compared to the CNN [21] and VGG-16 [22]. Precision value of 93% and recall of 92% for the proposed modified VGG-19 method predicted successfully in above figure 15.

5 Conclusion

In this research, a Modified VGG-19 model is proposed for the classification of TM images, achieving a high accuracy of 92.09% using Python. The preprocessing stage effectively enhances image quality by removing noise and black margins through data augmentation and bilateral filtering. The segmentation process is refined using fuzzy C-means clustering with optimized fuzziness parameters and cluster numbers. Furthermore, GLCM-based feature extraction captures the essential texture properties of TM images. The proposed Modified VGG-19 classifier demonstrates superior performance, highlighting its potential for accurate and efficient TM image classification.

References

1. Pratap Sriram Sundar; Chandan Chowdhury; Sagar Kamarthi, Year: 2021, "Evaluation of human ear anatomy and functionality by axiomatic design", Biomimetics, Vol: 6, no: 2, pp. 31.

2. Devon Livingstone; Justin Chau, Year: 2020, "Otoscopic diagnosis using computer vision: An automated machine learning approach", The Laryngoscope, Vol: 130, no: 6, pp. 1408-1413.

3. Alisha Prasad; Syed Mohammad Abid Hasan; Manas Ranjan Gartia, Year: 2020, "Optical identification of middle ear infection", Molecules, Vol: 25, no: 9, pp. 2239.

4. Zuwei Cao; Feifan Chen; Emad M. Grais; Fengjuan Yue; Yuexin Cai; De Wet Swanepoel; Fei Zhao, Year: 2023, "Machine learning in diagnosing middle ear disorders using tympanic membrane images: a meta-analysis", The Laryngoscope, Vol: 133, no: 4, pp. 732-741.

5. Hayoung Byun; Sangjoon Yu; Jaehoon Oh; Junwon Bae; Myeong Seong Yoon; Seung Hwan Lee; Jae Ho Chung; Tae Hyun Kim, Year: 2021, "An assistive role of a machine learning network in diagnosis of middle ear diseases", Journal of Clinical Medicine, Vol: 10, no: 15, pp. 3198.

6. Masaki Ogawa; Masaya Kisohara; Tatsuhito Yamamoto; Shunsuke Shibata; Yoshinao Ojio; Kanako Mochizuki; Ayame Tatsuta; Shinichi Iwasaki; Yuta Shibamoto, Year: 2022, "Utility of unsupervised deep learning using a 3D variational autoencoder in detecting inner ear abnormalities on CT images", Computers in Biology and Medicine, Vol: 147, pp. 105683.

7. Mohammed J. Abdulaal; Ibrahim M. Mehedi; Abdulah Jeza Aljohani; Ahmad H. Milyani; Mohamed Mahmoud; Manish Kumar Sahu; Abdullah M. Abusorrah; Rahtul Jannat Meem, Year: 2022, "Intelligent Control Techniques for the Detection of Biomedical Ear Infections", Computational Intelligence and Neuroscience, Vol: 2022, no: 1, pp. 9653513.

8. Tien Tran Van; Mi Lu Thi Thao; Linh Bui Mai Quynh; Cat Phan Ngoc Khuong; Linh Huynh Quang, Year: 2020, "Application of multispectral imaging in the human tympanic membrane", Journal of Healthcare Engineering, Vol: 2020, no: 1, pp. 6219845.

9. Dahye Song; In Sik Song; Jaeyoung Kim; June Choi; Yeonjoon Lee, Year: 2022, "Semantic Decomposition and Anomaly Detection of Tympanic Membrane Endoscopic Images", Applied Sciences, Vol: 12, no: 22, pp. 11677.

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10. Jingyang Hu; Hongbo Jiang; Daibo Liu; Zhu Xiao; Hangcheng Cao; Yue Qi; Schahram Dustdar; Jiangchuan Liu, Year: 2023, “EarSonar: An Acoustic Signal-Based Middle-Ear Effusion Detection Using Earphones”, In 2023 IEEE 43rd International Conference on Distributed Computing Systems (ICDCS), pp. 225-235.

11. Robin Guillard; Adam Hessas; Louis Korczowski; Alain Londero; Marco Congedo; Vincent Loche, Year: 2023, “Comparing Clustering Methods Applied to Tinnitus within a Bootstrapped and Diagnostic-Driven Semi-Supervised Framework”, Brain Sciences, Vol: 13, no: 4, pp. 572.

12. Jiuling Weng; Shujin Xue; Xingmei Wei; Simeng Lu; Jin Xie; Ying Kong; Mengya Shen; Biao Chen; Jingyuan Chen; Xinyue Zou; Xinyi Zhang; Zhencheng Gao; Ping Liu; Ying Shi; Danmo Cui; Yongxin Li; Haihui Wang, Year: 2024, “Machine learning-based prediction of the outcomes of cochlear implantation in patients with inner ear malformation”, European Archives of Oto-Rhino-Laryngology, pp. 1-11.

13. J. Gerb; S. A. Ahmadi; E. Kierig; B. Ertl-Wagner; M. Dieterich; Valerie Kirsch, Year: 2020, “VOLT: a novel open-source pipeline for automatic segmentation of endolymphatic space in inner ear MRI”, Journal of neurology, Vol: 267, pp. 185-196.

14. Wensheng Li; Jie Zhang; Jianlin Guo; Xiaoxu Wang; Guangyuan Xu; Yun Peng; Liyun Tu, Year: 2020, “Automated Detection and Classification of Pediatric Middle Ear Diseases from CT using Entropy Projection and Feature Interaction”, In 2024 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), pp. 2156-2163.

15. Farzana R. Zaki; Guillermo L. Monroy; Jindou Shi; Kavya Sudhir; Stephen A. Boppart, Year: 2024, “Texture-based speciation of otitis media-related bacterial biofilms from optical coherence tomography images using supervised classification”, Journal of Biophotonics, Vol: 17, no: 10, pp. e202400075.

16. Mohammad Azam Khan; Soonwook Kwon; Jaegul Choo; Seok Min Hong; Sung Hun Kang; Il-Ho Park; Sung Kyun Kim; Seok Jin Hong, Year: 2020, “Automatic detection of tympanic membrane and middle ear infection from oto-endoscopic images via convolutional neural networks”, Neural Networks, Vol: 126, pp. 384-394.

17. Erdal Başaran; Zafer Cömert; Yüksel Çelik, Year: 2020, “Convolutional neural network approach for automatic tympanic membrane detection and classification”, Biomedical Signal Processing and Control, Vol: 56, pp. 101734.

International Journal of Advanced Trends in Engineering and Management (IJATEM)
Vol. 03 (12), December 2024, pp. 39-55

18. Michelle Viscaino; Juan C. Maass; Paul H. Delano; Fernando Auat Cheein, Year: 2021, “Computer-aided ear diagnosis system based on CNN-LSTM hybrid learning framework for video otoscopy examination”, IEEE Access, Vol: 9, pp. 161292-161304.

19. Ankit Kumar Singh; Ajay Singh Raghuvanshi; Anmol Gupta; Harsh Dewangan, Year: 2023, “A Deep Learning Approach to Computer-Aided Screening and Early Diagnosis of Middle Ear Disease”, In International Conference on Advances in Data-driven Computing and Intelligent Systems, pp. 309-328.

20. Murat Uçar; Kemal Akyol; Ü. M. İ. T. Atila; Emine Uçar, Year: 2022, “Classification of different tympanic membrane conditions using fused deep hypercolumn features and bidirectional LSTM”, IRBM, Vol: 43, no: 3, pp. 187-197.

21. Michelle Viscaino; Matias Talamilla; Juan Cristóbal Maass; Pablo Henríquez; Paul H. Délano; Cecilia Auat Cheein; Fernando Auat Cheein, Year: 2022, “Color dependence analysis in a CNN-based computer-aided diagnosis system for middle and external ear diseases”, Diagnostics, Vol: 12, no: 4, pp. 917.

22. Zheng Wang; Jian Song; Ri Su; Muzhou Hou; Min Qi; Jianglin Zhang; Xuewen Wu, Year: 2022, “Structure-aware deep learning for chronic middle ear disease”, Expert Systems with Applications, Vol: 194, pp. 116519.