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# Classification of Otoendoscopic Images with the Developed Textural Based Artificial Intelligence Model

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***Abstract*** – Many ear diseases can be diagnosed with the findings obtained by otoendoscopic examination, thus enabling early diagnosis and treatment. The inadequacy of accurate diagnosis rates in primary health care institutions and the difficulties in reaching otolaryngologists in rural areas can cause delays in the diagnosis of otological pathologies and sometimes complications. These obligatory needs make it even more important to use computer-aided systems to accurately identify ear diseases. In this paper, a textural-based hybrid model has been developed for the classification of otoscope eardrum images. In the developed model, feature extraction was performed using LBP and HOG methods. From the features obtained from the feature maps obtained by the LBP and HOG methods, 500 features were selected each by using the Relief method. After the selected features were combined, the combined feature map was classified at different classifiers accepted in the literature. In the study, an accuracy value of 93.8% was obtained. This result demonstrates the potential of the suggested methodology for categorizing otoscope eardrum images.

*Keywords – Otoendoscopic Images, LBP, HOG, Relief, Classifiers*

## I. Introduction

The tympanic membrane (TM) is an important anatomical structure that separates the outer ear and middle ear. The TM is responsible for transmitting the sound transmitted through the auricle and external auditory canal to the ossicles and cochlea in the middle ear. Infections and traumas such as acute otitis media (AOM), otitis media with effusion (OME), and chronic otitis media (COM) may cause pathological structural changes in TM, resulting in impaired sound conduction and conductive hearing loss. The most important factor affecting vibration for sound transmission in TM is the thickness of the TM [1]. Otoscopic examination is an indispensable step of ear examination for visualization and accurate evaluation of the external auditory canal, TM, and middle ear. It is used to identify common conditions such as infection (otitis externa, AOM, COM), OME, perforation, cholesteatoma, tympanosclerosis, foreign body, tympanostomy tube presence/position, and cerumen. With the use of endoscopes in otolaryngology clinics since 1990, the use of otoscopic examination and some surgical interventions with the help of endoscopes has increased over time [2]. Images obtained from otoscopy or otoendoscopy provide important information for the diagnosis of otological diseases.

Ear exams are usually performed in primary care by local public health workers, general practitioners, and emergency physicians. According to the findings, patients can be referred to higher centers for further examination and treatment by ENT specialists for evaluation. Diagnostic accuracy in classical otoscopic or otoendoscopic examination differs between physicians. Oyehumi et al. reported that there were differences between groups in the correct diagnosis rates in otoscopic examination in groups consisting of pediatricians, family physicians, and otolaryngologists and that there was an increase in the diagnostic accuracy rates in all groups after the groups used a simulation training tool. According to this result, they emphasized the importance of education and the use of an additional diagnostic tool to increase the accuracy of diagnosis in otoendoscopic images [3].

Furthermore, primary care doctors routinely misdiagnose a variety of otological disorders. According to one study, pediatricians had a 51% accuracy rate for identifying acute otitis media and otitis media with effusion, general practitioners had a 44% accuracy rate, and otolaryngologists had a 74% accuracy rate [4]. These results showed that there is a need for additional diagnostic tools in order to make the evaluation of pathologies that require expertise in rural areas more healthily. Telehealth, which is defined as the use of telecommunications to support patient care remotely, can increase access for rural people, lessen the burden of postoperative and follow-up care, shorten wait times, and save the healthcare system a lot of money [5].

The inadequacy of diagnosis rates in primary health care institutions, the importance of otoscopy, and the difficulties in reaching specialist physicians bring up the use of computer-aided systems in the correct definition of ear diseases [6]. Applications for artificial intelligence are ones that have gained popularity recently and are used in medicine to diagnose a variety of illnesses. The diagnosis of numerous ailments, including ear disorders, breast cancer, lung cancer, Alzheimer's disease, skin cancer, Covid-19, and pneumonia, has been studied in the literature utilizing AI techniques [7-10]. Through computer-aided systems, it is intended to speed up the process of disease diagnosis and raise the accuracy of otological pathology diagnosis. Artificial intelligence is believed to be helpful in reducing individual errors and lightening the workload of doctors. In areas without access to ENT specialists, we believe that these artificial intelligence-based solutions can assist general practitioners in identifying otological disorders.

In this paper, we sought to assess the usefulness of AI modeling for characterizing otoendoscopic images.

In the continuation of the article, the Material and Methods section is included in the second section, the Experimental Results section is included in the third section, and the Conclusion section is included in the last section.

## II. MATERIALS AND METHOD

In this section, the dataset used in the study, the methods used, and the proposed model are examined.

### A. *Dataset*

The dataset used in the study is a public dataset. The relevant data set was created using patient images from Van Akdamar Hospital between 2018-2019. The images in the relevant dataset were obtained from patients aged 2 to 71 years. There are 7 classes in the related data set. There are images of different diseases in 6 classes, and normal images in 1 class [11,12]. The classes and image numbers in the relevant data set are presented in Table 1.

Table 1. Number of images in the dataset

| | |
|---|---|
| Normal | 154 |
| AOM | 69 |
| Earwax | 21 |
| Miringoskleroz | 4 |
| Tympanostomy Tubes | 2 |
| CSOM | 14 |
| Otitis Externa | 18 |

Examples from the images in the dataset are presented in Figure 1.

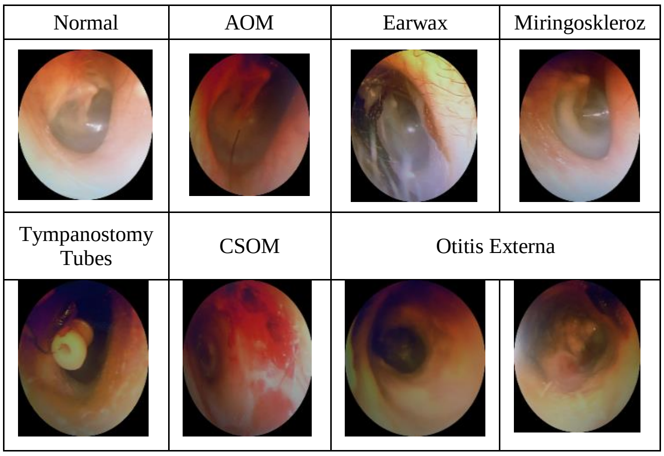


Fig. 1 Example of images of the dataset

Due to the low number of images in some classes in the study, 4 classes were used in the study. Images in these classes are augmented using data augmentation methods. The images in the dataset created after the data augmentation step were classified using the proposed model.

### B. *Proposed Model*

A textural-based model has been developed for the classification of otoendoscopic images. In the developed model, feature extraction was performed using Local Binary Pattern (LBP) [13] and Histogram of Gradients (HOG) [14] methods. From each of the feature maps obtained by LBP and HOG methods, 500 features were selected by the Relief method. After the selected features were combined, they were classified into different classifiers accepted in the literature. These classifiers are Fine Tree(FT) [15], Linear Discriminant (LD) [16], Naive Bayes (NB) [17], Support Vector Machine (SVM) [18], K-Nearest Neighbors (KNN) [19], and Ensemble Suspace (ES) [20].

While the number of features obtained using the LBP method is 2891, the number of features obtained using the HOG method is 1296. In the proposed model, 500 features are selected from each feature map and it is aimed to make the model work faster and more effectively. The block diagram of the developed architectures is presented in Figure 2.

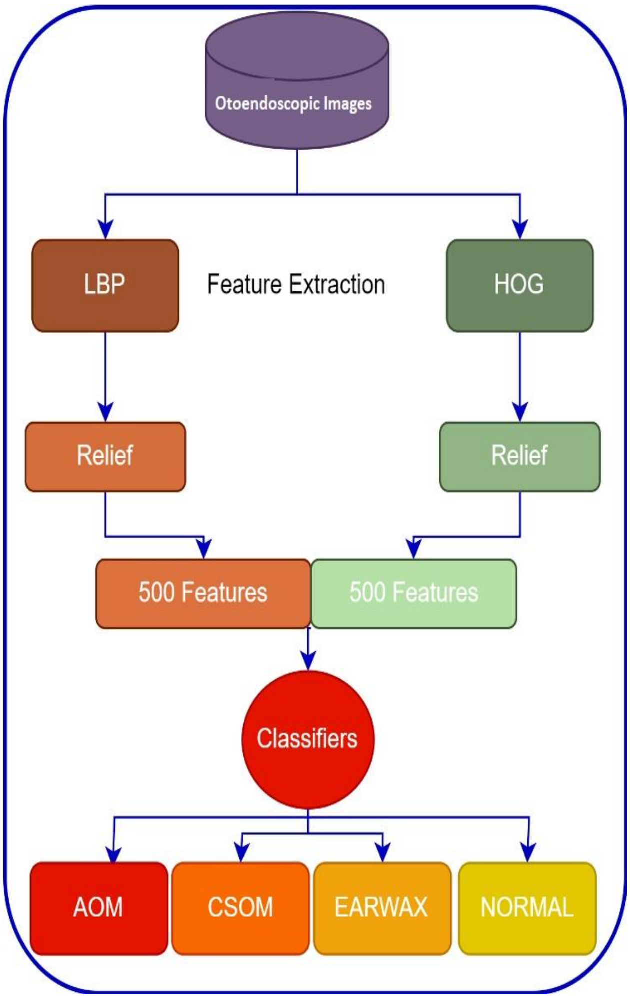


Fig. 2 Diagram of the proposed model

Thanks to the artificial intelligence-based model proposed for the classification of otoendoscopic images, the images in the data set are divided into 4 classes. These classes are AOM, CSOM, EARWAX, and NORMAL.

## III. Results

A texture-based model has been developed to classify the images in the dataset consisting of otoendoscopic images. The developed model was compared with LBP and HOG methods in different classifiers. The application results were taken in a Matlab environment. The computer used in the study is a computer with an i7 processor, 8 GB of RAM, and a Windows operating system.

In the paper, firstly, the feature map of the otoendoscopic images in the dataset was obtained by using the LBP method. The obtained feature map was classified at 6 different classifiers that are frequently used in the literature. The accuracy values obtained in these classifiers are presented in Table 2.

Table 2. Classification of the feature map obtained by LBP in different classifiers

| | |
|---|---|
| **FT** | 70.8% |
| **LD** | 86.3% |
| **NB** | 82.6% |
| **SVM** | **91.4%** |
| **KNN** | 88.7% |
| **ES** | 89.9% |

When Table 2 is evaluated, it can be noted that the SVM classifier achieved the maximum performance with 91.4%. The lowest accuracy value was obtained in the FT classifier at 70.8%.

In the study, firstly, the feature map of the otoendoscopic images in the data set was obtained by using the HOG method. The obtained feature map was classified at 6 different classifiers that are frequently used in the literature. The accuracy values obtained in these classifiers are presented in Table 3.

Table 3. Classification of the feature map obtained by HOG in different classifiers

| | |
|---|---|
| **FT** | 78.6% |
| **LD** | 87.5% |
| **NB** | 82.5% |
| **SVM** | **92.24%** |
| **KNN** | 90.4% |
| **ES** | 91.9% |

When Table 3 is evaluated, the highest performance of 92.24% was get in the SVM classifier. The lowest accuracy value was get in the FT classifier at 78.6%.

In the study, otoendoscopic images were classified using the last proposed method. 500 features were selected by the Relief method from each of the feature maps obtained using the LBP and HOG methods. After combining the selected features, a total of 1000 features were obtained. This feature map consisting of 1000 features has been classified at different classifiers. The accuracy values obtained in these classifiers are presented in Table 4.

Table 4. The accuracy values of the proposed method

| | |
|---|---|
| **FT** | 73.2% |
| **LD** | 88.0% |
| **NB** | 83.5% |
| **SVM** | **93.8**% |
| **KNN** | 92.6% |
| **ES** | 93.6% |

When Table 4 is evaluated, it can be shown that the SVM classifier achieved the maximum performance with 93.8%. The SVM classifier is followed by the ES classifier with 93.6%, 92.6% KNN, 88.0% LD, 83.5% NB, and 73.2% FT.

## IV. DISCUSSION

The reason why otoendoscopic images are evaluated incorrectly is mostly due to the physician's inexperience in using otoscopy or otoendoscopy [21,22]. The accuracy of otoscopic examinations performed by health workers and general practitioners in primary healthcare institutions in rural areas depends on the education and experience of the person performing the examination. There are studies in the literature reporting that general practitioners make the correct diagnosis between 30% and 67.5% compared to otolaryngologists for certain diseases [6]. Training is offered to improve diagnostic accuracy, including practical training led by otolaryngologists, simulation using artificial ear models, and online teaching modules contrasting normal and aberrant otoscopic TM images. Comparisons made before and after training sessions show short-term improvements in diagnostic performance by looking at otoendoscopic images, but these benefits cannot be sustained in the long term and may decrease over time to initial evaluations [3,23]. If early diagnosis and appropriate treatment is not performed, the existing pathology may worsen and even irreversible complications may occur [24]. For these reasons, new diagnostic strategies are needed to facilitate the early diagnosis and treatment of otological pathologies.

These artificial intelligence-based models are an emerging technology that can be used to diagnose ear diseases using otoendoscopic images [25]. The use of these artificial intelligence models in addition to otoendoscopy in primary care helps to diagnose otological diseases in rural and remote areas where access to ENT specialists is limited.

The main limitation of the study is the small number of data and the inability to obtain data from different centers in the data set. It is among our goals to obtain data from different centers in the future and produce more successful results.

## V. CONCLUSION

Because ear illnesses are widespread and can have serious consequences if neglected, early diagnosis and treatment are extremely important. The methodology we have put out for the diagnosis of otoendoscopic images will remove the variances in interpretation between physicians while also allowing the patient's therapy to begin sooner.

Recent years have seen a rise in the usage of artificial intelligence-based techniques, particularly in the biomedical industry. For the classification of otoendoscopic images, a textural-based hybrid model has been created in this study. A high accuracy value of 93.8% was achieved in the classification of otoendoscopic images by applying the created model. This result demonstrates the potential of the suggested approach for otoendoscopic image classification.


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## CONFLICT OF INTEREST

There is no conflict of interest

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