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Deep Learning Approaches for Otitis Media Classification: A Comprehensive Survey

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ABSTRACT

Middle ear infections known as Otitis Media (OM) are classified as inflammatory diseases. It is one of the most prevalent illnesses affecting young children and the second-largest cause of hearing loss. The OM can go away on its own without creating any problems, but it can also result in hearing loss and have long-lasting effects. Diagnostic techniques include tympanometry, audiometry, and (pneumatic) otoscopy. Accurate and timely classification of OM is essential for effective diagnosis and treatment. Recent advancements in Artificial Intelligence (AI) have introduced innovative methods for classifying Otitis Media, significantly enhancing diagnostic accuracy and supporting healthcare professionals in clinical settings. The primary objective of this survey is to provide a comprehensive overview of recent strategies and techniques for the classification of Otitis Media using artificial intelligence approaches. This includes an in-depth analysis of existing OM classification systems, highlighting the evolution of methods and examining their respective strengths and limitations. This survey article consolidates recent insights on Otitis Media classification, serving as a valuable resource for researchers, clinicians, and healthcare stakeholders. It emphasises how crucial it is to use Deep Learning (DL) approaches to get beyond the difficulties posed by manual otoscopy, resulting in increased efficacy and accuracy in the identification of OM.

Keywords: *Otitis Media , Ear Infection, Deep Learning, Classification*.

1. INTRODUCTION

Otitis Media is a prevalent ear infection primarily affecting children, particularly in developing countries, where it accounts for numerous pediatric consultations. Defined as the inflammation of the middle ear mucosa, this condition poses considerable health risks, including serious complications that can arise from untreated cases. The World Health Organization identifies OM as one of the principal causes of preventable hearing loss, which has far-reaching implications on a child's language acquisition, communicative skills, cognitive functions and academic performance. Given its high prevalence and significant impact on childhood health, various classifications of OM have emerged to better understand the condition and tailor appropriate therapeutic strategies. OM can be categorized into several forms, including Acute Otitis Media (AOM) , Otitis Media with Effusion (OME) and Chronic Otitis Media (COM). AOM is characterised by a sudden onset of earpain, often due to a bacterial or viral infection. OME, commonly known as glue ear, involves the presence of fluid in the middle part of the ear without any signs of acute infection. Chronic otitis media can be identified by persistent inflammation and infection of the middle ear (Klien, 1994). The classification of OM serves practical purposes in guiding diagnosis and treatment. As childhood infections continue to pose global health challenges, utilizing those classifications can enhance pediatric healthcare strategies, ensuring that more children receive timely and effective care.

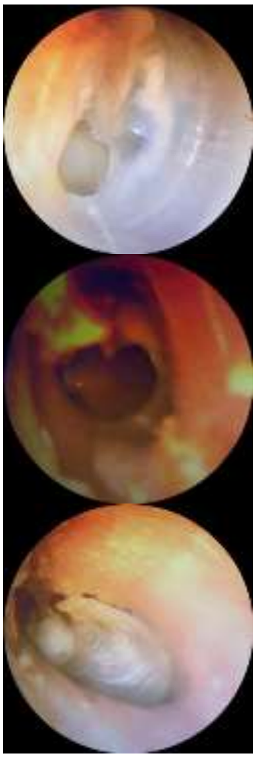
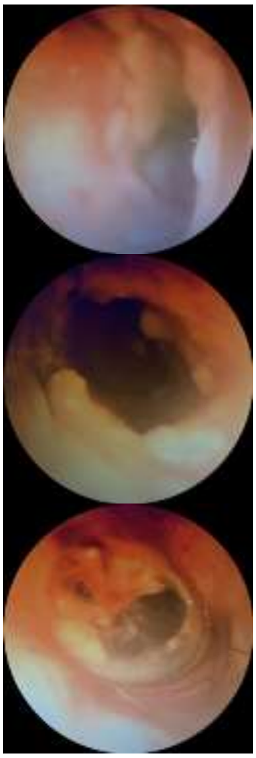
AOM	**COM**	**OME**	**NORMAL**
			

Figure 1. Examples of dataset images

Otoscopy plays a vital role in diagnosing ear infections and assessing ear health and hearing. It is a common practice among various healthcare professionals, including medical students, nurses, general practitioners, emergency medicine physicians, pediatricians, audiologists, and otolaryngologists. However, the effectiveness of otoscopic evaluations can be significantly influenced by the user's experience. Research indicates that non-experts often struggle to differentiate between various subtypes of ear diseases, which can hinder accurate diagnosis (Cha et al., 2021; Kleinman et al., 2021; Pichichero and Poole, 2005).

Otolaryngologists, with their specialized training, demonstrate a marked advantage over non-specialists in recognizing key clinical features and subtypes of ear conditions (Khan et al., 2020). Accurate identification of middle ear disorders is crucial for timely intervention, yet interpreting otoscopic findings can be complex.

To address these challenges, several AI-based applications have been developed, leveraging various methodologies. Deep learning algorithms have shown strong classification accuracy in this domain (Chelliah et al., 2023; Liu and Yen, 2024). Additionally, neural networks have been employed for precise classification tasks (Chelliah et al., 2023), while machine learning techniques have been utilized for image classification and other applications within computational intelligence (Singh and Vigila, 2023). These advancements aim to enhance diagnostic capabilities and improve patient outcomes in ear health.

To diagnose OM, the middle ear must be examined for signs of infection, fluid build-up, inflammation, or other abnormalities. In clinical practice, several diagnostic techniques are frequently applied. The most frequent technique for diagnosing OM is traditional otoscopy. To visually examine the ear canal and eardrum, one must use an otoscope, portable equipment with a light and enlarging lens. The medical expert looks for indications of inflammation, perforation, or fluid build-up by assessing the TM's (eardrum) colour, location, and integrity. Tympanometry monitors the eardrum's movement in response to variations in air pressure. This examination evaluates middle ear functionality and looks for anomalies such as fluid build-up or eustachian tube malfunction. Audiologists assess a person's ability to hear with different frequencies and intensities during an audiometry test. It can help identify hearing loss caused by OM or other conditions.

To diagnose otitis media, it is essential to examine the middle ear for signs of infection, fluid accumulation, inflammation, or other abnormalities. In clinical practice, several diagnostic techniques are commonly employed, with traditional otoscopy being the most prevalent method. This technique involves using an otoscope, a portable device equipped with a light and magnifying lens, to visually inspect the ear canal and eardrum. The medical professional looks for signs of inflammation, perforation, or fluid accumulation by evaluating the color, position, and integrity of the tympanic membrane. Another diagnostic tool is tympanometry, which assesses the movement of the eardrum in response to changes in air pressure. This test evaluates the functionality of the middle ear and can identify issues such as fluid buildup or dysfunction of the eustachian tube. Additionally, audiometry tests are conducted by audiologists to evaluate a person's hearing ability across various frequencies and intensities. This assessment can help detect hearing loss associated with OM or other conditions.

2. LITERATURE REVIEW

This comprehensive paper surveys and analyzes research specifically focused on the identification and classification of otitis media using computer vision techniques. The role of AI in OM classification is becoming increasingly important, offering significant potential to improve diagnostic accuracy and efficiency. AI methodologies, including machine learning and deep learning algorithms, are capable of analyzing and interpreting otoscopic images and other relevant data to aid in the classification of various types and stages of OM (Wu et al., 2021; Lee et al., 2019; Wang et al., 2020).

Deep learning approaches have emerged as powerful tools for classifying otitis media, providing the potential for accurate and automated diagnoses. These methods facilitate the diagnosis and classification of various types and stages of OM by analyzing a diverse range of data sources, including otoscopic images, patient demographics, clinical features, and medical histories. Recent research has explored the application of DL algorithms in the classification of OM, yielding promising results that highlight the potential of these techniques to enhance diagnostic accuracy and efficiency.

Deep learning, a subset of machine learning, has garnered significant attention in the classification of otitis media due to its capability to generate hierarchical representations from unstructured data. One commonly used DL architecture for this purpose is the Convolutional Neural Network (CNN), which is effective in extracting distinguishing features from otoscopic images. By training on large datasets, CNN algorithms can learn to differentiate between images of normal ears and those exhibiting abnormalities (Başaran et al., 2022; Binol et al., 2022; Myburgh et al., 2016).

2.1. Overview of the Otitis Media Classification

This section outlines a comprehensive methodology for classifying otitis media (OM), detailing a systematic approach that encompasses pre-processing, feature extraction, model training, and evaluation.

The methodology consists of several interconnected steps. Initially, a diverse and representative dataset is gathered, comprising otoscopic images and related data that cover various types and stages of OM, along with images of normal ears for comparative analysis. Once the dataset is collected, it undergoes pre-processing to eliminate artifacts and noise, employing techniques such as image enhancement and normalization.

Following pre-processing, relevant features are extracted from the cleaned data, including color histograms, texture descriptors, and shape characteristics, which aid in distinguishing between different types of OM. Subsequently, a feature selection process is implemented to identify the most informative and discriminative features, thereby improving the model's efficiency and accuracy (Camalan et al., 2020).

As the next step, an appropriate classification algorithm is chosen—ranging from traditional machine learning methods such as Support Vector Machines (SVM), Random Forests, and K-Nearest Neighbors (KNN), to deep learning architectures like Convolutional Neural Networks (CNNs). The dataset is split into training and validation sets to develop and fine-tune the model. Evaluation metrics such as accuracy, precision, recall, and F1-score are employed to assess performance. To ensure robustness and real-world applicability, the model is further validated on an independent clinical dataset, in collaboration with medical professionals and otolaryngologists, highlighting its potential for integration into healthcare systems. The general methodology for OM classification is shown in Figure 2.

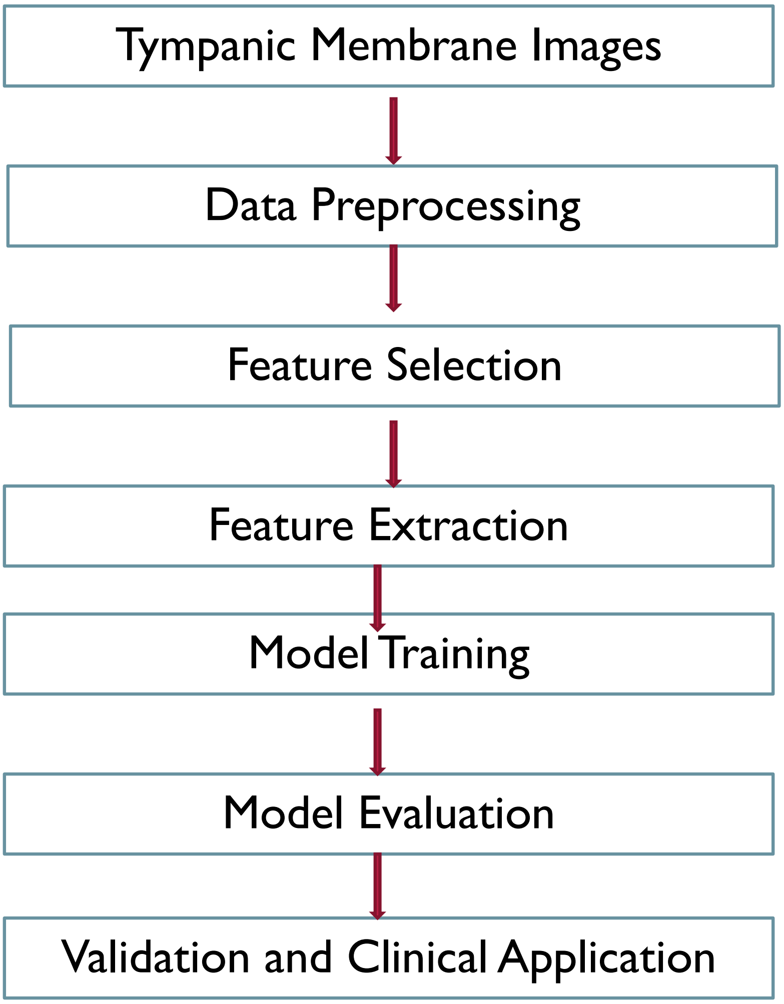


Figure 2. Work Flow For OM Classification

2.2. Deep Learning Approaches for Otitis Media Classification

Deep learning (DL) has emerged as a powerful tool in the classification of Otitis Media (OM), a prevalent infection of the middle ear. By leveraging deep neural networks, DL techniques can autonomously learn complex patterns and extract discriminative features from large datasets of otoscopic images—an essential diagnostic resource in clinical practice. These networks are trained to identify specific visual markers and pathological patterns associated with various forms of OM. Notably, DL models have shown high accuracy in differentiating between normal ear conditions and distinct OM types, such as Acute Otitis Media (AOM) and Otitis Media with Effusion (OME), owing to their ability to model intricate spatial and contextual relationships within the data. The application of DL in OM classification not only enhances early detection but also reduces diagnostic subjectivity and improves overall accuracy. This advancement paves the way for more timely and precise medical interventions, ultimately contributing to better patient care and outcomes (Habib et al., 2022).

Wang et al. (2022) tackle the issue of dataset imbalance in otoscopic video classification, where normal cases dominate due to routine bilateral ear exams and symptom overlap with non-ear conditions. They propose a Unified Anomaly Detection (UAD) framework that maps normal videos to minor anomalies and abnormal ones to major anomalies. Using a large normal-only training set (Dtrain) and a mixed testing set (Dtest), the system comprises three components: eardrum detection, representation learning, and anomaly detection. A CNN, trained with cross-entropy and L1 loss, localizes the eardrum and classifies frames. For feature representation, they employ a mean-shifted contrastive learning approach that strengthens the separation between normal and abnormal samples by maximizing angular distances in the feature space, thereby enhancing classification performance.

From a multi-year retrospective study, images from 2,022 patients who visited Sun Yat-sen Memorial Hospital in China were collected and labeled using clinical diagnoses, surgical findings, and pathology reports (Cai et al., 2021). A two-stage classification model was employed: Image-Net acted as a global classifier, using Class Activation Maps (CAMs) to highlight key regions, which then guided a focal model trained on these discriminative patches. Final predictions were made by averaging outputs from both models. ResNet27 and Inception-V3 were evaluated using patient-level triple cross-validation and the Adam optimizer. Sundgaard et al. (2021) emphasized the strength of deep embedding representations over traditional softmax outputs, using metric learning losses like contrastive, triplet, and N-pair loss to enhance class separation in the embedding space. Zafer (2020) demonstrated the effectiveness of combining deep features from DCNNs with classical classifiers, with VGG-16 achieving 93.5% accuracy. When integrated with an SVM, the model reached outstanding results: 99.47% accuracy, 99.35% sensitivity, and 99.77% specificity.

Wu et al. (2021) used otoscope images of children under 18 from Shenzhen Children's Hospital, captured via smartphone-connected otoendoscopes. They applied transfer learning with pre-trained CNNs (Xception and MobileNet-V2) fine-tuned on the otoscope data, using data augmentation to enhance training diversity. Crowson et al. (2021) analyzed intraoperative middle ear videos from pediatric surgeries to diagnose Middle Ear Effusion (MEE) using CNNs. Pre-processing steps were applied to improve video quality, leading to high diagnostic accuracy. Tsutsumi et al. (2021) also used transfer learning with Xception and MobileNet-V2, fine-tuning pre-trained ImageNet models to classify ear videos, aided by quality-enhancing pre-processing. Basaran et al. (2020) used various CNNs (AlexNet, VGG, GoogLeNet, ResNet) to classify Tympanic Membrane (TM) images. Pre-processing included histogram equalization and resizing, while data augmentation expanded the dataset from 282 to 1692 samples. They also applied Faster R-CNN for object detection.

Cai et al. (2021) applied a Gaussian filter to reduce noise in image data during ADC conversion. They developed a hybrid deep model using EfficientNetB0 and DenseNet201, with SVM and other classifiers (Decision Trees, KNN, Naive Bayes, etc.) used for feature classification. Eroğlu and Yildirim (2022) combined EfficientNetB0, DarkNet53, and DenseNet201 to extract diverse eardrum features. Neighbourhood Component Analysis (NCA) was used for feature selection and dimensionality reduction, improving diagnostic accuracy. Mohammed et al. (2022) integrated CNN with BiLSTM, using EfficientNetB0 for feature extraction and Bayesian optimization to fine-tune LSTM parameters. A dropout layer was used to prevent overfitting. Akyol et al. (2024) proposed a CNN-based ensemble framework to classify TM conditions (normal, earwax, myringosclerosis, COM) using public ear imagery data. A voting ensemble (hard and soft voting) improved classification accuracy and stability. Habib et al. (2022) used AI to classify otoscopy images for OM diagnosis. AI outperformed human experts (93.4% vs. 73.2% accuracy), showing promise for use in primary and point-of-care settings.

Sundgaard et al. (2022) focused on classifying Otitis Media (OM), including Acute OM (AOM), Otitis Media with Effusion (OME), and No Effusion (NOE), using wideband tympanometry (WBT) data. They first separated OM and NOE, then used a custom 2D CNN—based on AlexNet architecture—to classify WBT values without requiring pre-training. The network was trained end-to-end with the Adam optimizer and binary cross-entropy loss, applying a 0.5 threshold for final classification. GradCAM-generated saliency maps highlighted key input features influencing the model's decisions. Choi et al. (2022) developed a multi-task deep learning model using EfficientNet-B4 with transfer learning from ImageNet. Images were classified into a main class (OME, COM, None) and four subcategories (attic cholesteatoma, myringitis, otomycosis, ventilating tubes). The model was trained with categorical cross-entropy loss, and predictions were made based on the top softmax score. Xiao et al. (2019) enhanced OM diagnosis using Fine-Grained Visual Classification (FGVC) on endoscopic images of the tympanic membrane. Their weakly-supervised method used an image-level CNN to generate saliency maps that guided the selection of key local patches. These patches were then used to train a patch-level CNN. By combining outputs from both networks, the model achieved effective classification without needing detailed part annotations, showing strong performance on real clinical data.

Monroy et al. (2019) proposed an automated system using OCT imaging to classify ear conditions into normal, biofilm-only, and biofilm with fluid, achieving over 90% accuracy. The system is designed for easy integration into clinical settings to assist practitioners at all skill levels. Chen et al. (2022) used CNN models (AlexNet, VGG16, GoogLeNet, ResNet50) with otoscope images to classify normal vs. abnormal middle ear conditions. Image enhancement and feature selection (NCA) improved performance, with VGG16 combined with SVM reaching 81.7% accuracy. Zeng et al. (2022) used deep learning and logistic regression to predict Conductive Hearing Loss (CHL) from 2,790 otoscopic images. The model achieved an AUC of 0.74, 81% accuracy, and an F1-score of 0.89, supporting its clinical applicability across a wide age range. Uçar et al. (2022) developed a hybrid deep learning model combining VGG16 and Bi-LSTM to classify TM conditions (earwax, myringosclerosis, COM, normal) using 880 public otoscopy images. The model utilized hyper-column features and performed well across RGB, HSV, and HED color spaces, achieving 99.06% accuracy, 98.13% sensitivity, and 99.38% specificity.

Alhudhaif et al. (2021) integrated CBAM, residual blocks, and the hyper-column method into their model, achieving 98.26% accuracy, 97.68% sensitivity, and 99.30% specificity—outperforming pre-trained CNNs. U-Net was used to extract middle ear (ME) patches, with structure-constrained feature fusion and a Graph Isomorphism Network (GIN) enabling accurate (96.36%) classification of CSOM and MEC (Cao et al., 2023).

Kim et al. (2023) combined endoscopic TM images and patient-specific pure-tone audiometry (PTA) data in an ANN to classify ear states. The model, trained with cross-entropy loss and Adam optimizer, was validated through internal, external, and pooled assessments using CNNs. Zafer (2020) developed DL models using various neural networks and validated them with fivefold cross-validation, bootstrapping, and statistical comparisons against clinical standards. Zeng et al. (2022) used refined DenseNet-BC169 and BC1615 models with transfer learning to classify eight ear disorders based on eardrum and auditory canal features, achieving 95.59% accuracy. Çalışkan (2022) applied VGG16 and SVMs on otoscope images in a three-stage process. The fc6 layer yielded the best results with 82.17% accuracy, 71.43% sensitivity, and 90.62% specificity, highlighting VGG16's potential in OM diagnosis.

3. EVALUATION TECHNIQUES FOR OTITIS MEDIA CLASSIFICATION

3.1. Evaluation

The assessment of experimental studies employs a confusion matrix, which includes four key performance metrics: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). These metrics help evaluate the accuracy of positive and negative predictions. The F1-Score can be derived from this matrix, and equations (1) to (4) are used to calculate accuracy, sensitivity, and specificity (Başaran et al., 2020).

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{TP+TN}}{\boldsymbol{TP+TN+FP+FN}} \quad (1)$$

$$\boldsymbol{Sensitivity} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FN}} \quad (2)$$

$$\boldsymbol{Specificity} = \frac{\boldsymbol{TN}}{\boldsymbol{TN+FP}} \quad (3)$$

$$\boldsymbol{F1-Score} = \frac{\boldsymbol{2*TP}}{\boldsymbol{2*TP+FP+FN}} \quad (4)$$

3.2. Deep Learning techniques in Otitis Media classification

Deep learning (DL) has emerged as a powerful tool for classifying otitis media (OM) by automatically learning complex patterns from data. Convolutional Neural Networks (CNNs) are particularly effective in analyzing otoscopic images to enhance classification accuracy. Viscaino et al. (2022) demonstrated that color wavelengths impact CNN-based OM classification. Their model, integrated into a computer-aided diagnosis system, classified four ear conditions (normal, COM, COME, earwax plug) using single-channel images. The green channel model performed best, achieving 92% accuracy, 85% sensitivity, 95% specificity, 86% precision, and an 85% F1-score—significantly improving diagnostic accuracy over non-specialist physicians.

Table 1 summarizes various deep learning studies focused on otitis media (OM) classification, detailing the authors, methodologies, number of images utilized, number of classes, accuracy, and the strengths and weaknesses of each study.

Table 1. Summary of the studies using Deep Learning Mechanism

Author & Year	**Method Used**	**No of Images**	**Classes**	**Accuracy**	**Strength**	**Weakness**
Khan 2020	DenseNet	282	2	95	High Accuracy	Limited Dataset
(Byun et al., 2021)	ResNet18 + Shuffle	2272	4	93	Enhanced Feature Extraction	Computational Complexity
(Cai et al., 2021)	Two CNNs+two-stage classification pipeline	6066	4	96.8	Improved Classification Precision	Increased Model Complexity
(Sundgaard et al., 2022)	Contrastive loss, multi-class N-pair loss and triplet loss	1336	3	85	Robust Feature Discrimination	Training Instability
Bingol, (2022)	Efficientnetb0 and Densenet201	454	3	98.2	High Accuracy and Feature	Increased Model Complexity

					Extraction	
Mohammed et al., (2022)	CNN+LSTM	880	4	100	Enhanced Sequential Feature Learning	Increased Model Complexity
Sundgaard et al., (2022)	CNN+ Saliency maps	1014	2	92.6	Enhanced Interpretability	Unintuitive Visualizations
Choi et al., (2022)	Customized EfficientNet-B4	5000	8	98.26	High Diagnostic Accuracy	Model Complexity
Chen et al., (2022)	Different CNN Models	2820	3	98	Diverse Model Evaluation	Inconsistent Performance
Habib et al., (2022).	CNN, ANN, SVM, decision tree, KNN		2 3	90.7 97.2	Comprehensive Model Comparison	Inconsistent Performance
Cao et al., (2023)	ROI Network + structure-constrained deep feature fusion algorithm	998	2	96. 36	High Classification Accuracy	Model Complexity
Cao et al., (2023)	ML models	20254	2	-	Comprehensive Model Comparison	Inconsistent Performance
Kim et al., (2023)	CNN & PTA	1,180	3	99.5	Enhanced Diagnostic Accuracy	Limited Data Scope

Khan (2020) employed DenseNet for binary classification on 282 images, achieving 86.8% sensitivity, 93.5% specificity, and 95% accuracy. Tsutsumi et al. (2021) used ResNet-50, Inception-V3, Inception-ResNet-V2, and MobileNetV2 on 400 images across four classes, resulting in 55.3% sensitivity and 66% accuracy. Chen et al. (2022) reported a model with 96.7% sensitivity, 96.4% specificity, and 98% accuracy based on 2,820 images with three classes. These studies demonstrate the potential of deep learning in otitis media classification by effectively learning complex patterns from otoscopic images.

4. CONCLUSION

The literature review highlights the significant progress made in the field of Otitis Media classification, particularly through the application of artificial intelligence and machine learning techniques. Recent studies demonstrate the potential of deep learning models, especially convolutional neural networks , in achieving high accuracy for OM classification. However, there are still challenges, such as the need for large, labeled datasets to train the models. The risk of models becoming too focused on specific data (overfitting), and differences in performance across various patient groups and imaging methods. While deep learning models can perform well on training data, they may struggle to generalize to new, unseen data, particularly when training datasets are limited. Further research is needed to address these limitations and improve the generalizability of AI-driven OM classification systems

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