A comparative look at how emerging technologies evolve to managing otitis media

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ABSTRACT

Otitis media (OM) is an epidemic of middle ear infection in tens of millions of patients across the globe, most vulnerable of whom are children, with hearing loss and other negative consequences unless treated. Conventional diagnosis and treatment are marred by failure to diagnose, service shortage, and delayed diagnosis. This present paper is directed towards a comparative outlook of the newly emerging technologies, such as artificial intelligence (AI), machine learning, telemedicine, and wearable biosensors, that are revolutionizing the management of OM. We emphasize the way such devices enhance diagnostic accuracy, facilitate remote and real-time monitoring, and provide tailored treatment schemes. Our approach is more sophisticated compared to the currently available state-of-the-art methods reported in the literature based on real-time telemedicine systems, multimodal data fusion, and interpretable AI. Privacy issues of information, model generalizability issues, and technological adoption barriers are also discussed. The results also substantiate that adoption of these advanced devices can effectively reduce OM's burden globally and improve patient outcomes.

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1. INTRODUCTION

Hearing loss is an emergent public health issue, with the World Health Organization (WHO) indicating that an estimated 2.5 billion individuals worldwide suffer from some form of ear disorders, and over 700 million will need hearing rehabilitation by the year 2050 [1]. Otitis Media (OM), a variety of middle ear infection and effusion, is one of the most common conditions to affect children under three years of age. Otitis media (OM) at birth has been estimated to occur in five out of six children. OM is a valid indication for pediatric referral, antibiotic treatment, and surgery like tympanostomy tube insertion in developed countries [2]. OM has three clinical subtypes: acute otitis media (AOM), otitis media with effusion (OME), and chronic otitis media with effusion (COME). AOM usually presents in the form of otalgia, fever, and bulging TM, usually with bacterial infection and possible TM perforation with otorrhea [3]. Conversely, OME is usually asymptomatic and has TM retraction and middle ear effusion, and can result in temporary hearing loss. In the long term, unmanaged OME can cause retraction pockets and injury to ossicular chain [4]. Some chronic types of OM can have mucosal or squamous disease, active or inactive, which can have long-term implications for the auditory system [5]. Timely OM diagnosis by the clinician is required for proper treatment regimens, ranging from antibiotics, corticosteroids, ventilation tubes, or prevention measures like chemoprophylaxis and pneumococcal immunization. Yet precision is largely dependent on the experience and judgment of the clinician's interpretation of otoscopic or endoscopic examination results, including most importantly the TM status [6]. According to an estimate by the World Health Organization (WHO), nearly 2.5 billion individuals suffer from disorders of the ear and OM is one of the leading causes of hearing loss if not treated [1]. Traditional diagnosis using otoscopy and clinical evaluation only is often delayed by subjective interpretation as well as limited access to remote or resource-poor locations [7]. Recent advances in technology have greatly enhanced OM management. Artificial intelligence (AI) and machine learning (ML) are being more commonly used to automate the diagnosis of OM from otoscopic images, improving diagnostic accuracy and reliability [8]. Research has shown that AI is able to minimize misdiagnosis and aid healthcare workers, especially those working in primary and telemedicine clinics [9]. Handheld diagnostic instruments coupling tympanometry and acoustic reflectometry on handheld platforms enable the real-time, non-invasive measurement of middle ear function in early detection and ongoing monitoring of OM [10]. These technologies are especially valuable for pediatric presentations and where specialists' access is limited. Telemedicine has developed into a useful platform capable of providing remote otoscopic evaluations and consultations. This enables more accessibility while limiting clinic visits and expediting initiation of care [11]. The COVID-19 pandemic has accelerated the adoption of telehealth in managing OM, successfully demonstrating both feasibility and high patient satisfaction. In therapeutics, nanotechnology has developed new drug-delivery systems that have targets specific to the middle ear. Nanoparticles facilitate the localized delivery of antibiotics, enhancing treatment efficacy while minimizing systemic side effects [12]. Comparisons suggest a multidisciplinary approach with AI, sensor technology, telehealth, and new pharmacological treatments would provide comprehensive care of OM [13].

Table 1 introduces new developments in AI and ML are paving the way for the automation of ontological diagnosis and decreased variability between listeners. Previous AI-based models consisted mainly of static, rule-based classifiers that were inflexible in their design and did not generalize well to different clinical environments [14]. More recently, convolutional neural networks (CNNs) and deep learning models such as ResNet have shown that they can perform well in medical image classification, including the diagnosis of OM, reporting accuracy estimates ranging from 84% to 94% [15], [16]. However, existing models are typically trained on small datasets that have limited demographic representation, do not incorporate patient-specific clinical data from clinical care, and lack sufficient external validation [17].

Barring that, most of these models are image classification-only, without considering important patient history, symptomology, and clinical context data. Their exclusion restricts their diagnostic utility and relevance in clinical practice, particularly in complicated or unusual cases [18]. With enhanced diagnostic imaging in otology, this research is adding to the United Nations' Sustainable Development Goals—SDG 3 (Good Health and Well-being) and SDG 9 (Industry, Innovation, and Infrastructure)—by closing loopholes in low-cost and creative healthcare solutions [19].

Table 1. Comparative table of emerging technologies in otitis media management

Technology	Application	Advantages	Challenges	Key References
Artificial Intelligence (AI)	Automated diagnosis from otoscopic images	High accuracy, reduces subjective errors, supports telemedicine	Requires large, annotated datasets, data privacy concerns	[7], [13]
Portable Diagnostic Devices	Tympanometry, acoustic reflectometry on mobile	Real-time, non-invasive, convenient for continuous monitoring	Calibration, device cost, user training	[9]
Telemedicine	Remote diagnosis and consultation	Expands access to care, reduces patient travel	Internet connectivity, regulatory issues	[10]
Nanotechnology-based drug delivery	Targeted antibiotic delivery to the middle ear	Improved drug efficacy, reduced systemic side effects	Development cost, clinical validation needed	[12]

2. METHOD

The method adopted in this work combines deep learning-based image processing with clinical metadata to construct a reliable OM diagnostic system. The process is fourfold: i) data acquisition, ii) preprocessing, iii) model training and development, and iv) system testing. Figure 1 provides a system architecture overview.

2.1. Data acquisition

This research data was in two forms. The former type was the otoscopic images, high-quality images of the tympanic membrane (TM), which were obtained in publicly available data sources such as the TM-ImageNet and clinical otoscopic image dataset (COID), and augmented with anonymized clinical samples, supplied by the participating otolaryngology specialists and clinics [20]. The second data form was clinical metadata, which included patient demographics and clinical information (e.g., age), the medical history of a patient (i.e. whether or not there is a history of ear infections), the presenting symptoms (e.g. fever, ear pain, discharge), audiometric data, and medical diagnoses provided by the referring physician. These data sources were utilized in conjunction, since they offer a strong complementary data source which includes both clinical contextual data and visual clinical data that were needed in the development of diagnostic models [21]. For supervised learning, each sample was labelled with expert-reviewed OM sub-typing labels - AOM, OME, COME, and normal - for the ground truth in the training process.

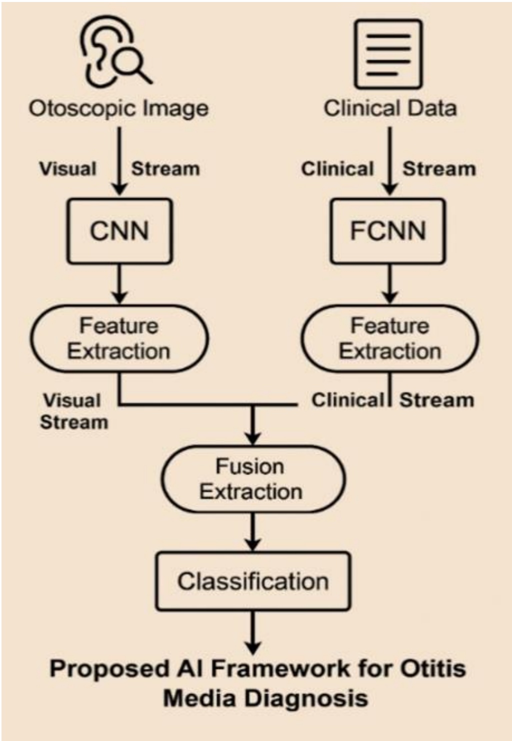

Figure 1. Proposed AI framework for otitis media diagnosis

2.2. Image preprocessing

In order to ensure data consistency and reduce the undesired variation, multiple preprocessing methods were applied in a systematic way. The initial step entailed the need to resize all otoscopic images to a standard size of 224 by 224 pixels so as to have a standard dataset. Thereafter, the images were histogram equalized to being able to see the outlines of the important objects more clearly. It was then followed by Gaussian filtering so that noise could be minimized without losing any significant structure in the images hence enhancing the quality further. In order to enhance the generalizability and reliability of the model under different conditions data augmentation methods like rotation, flipping, and scaling were used. All these actions led to the formation of a structured and homogeneous data set, which is a strong basis of successful model training and the correct assessment of performance [22].

2.3. Model development

The suggested diagnostic solution has a dual stream deep learning model that combines visual and clinical data to increase classification rates. To be used in the visual component, a convolutional neural network (CNN) called ResNet-50 that had been initially trained on a large dataset was further fine-tuned using otoscopic images that were collected. It was this experience which made the network familiar and memorized the visual features which were specific in the tympanic membrane. This visual stream outcome leads to the establishment of a probability distribution that will demonstrate the likelihood of various types of otitis media (OM) and it is an essential part of the general diagnostic decision-making process [23]. The clinical stream involves the use of a fully connected neural network (FCNN) to run structured clinical metadata to learn meaningful representations using patient-specific variables. In a fusion layer, the feature vectors of the two streams are concatenated and this enables full visual and contextual information to be represented [24]. The concatenated features then pass through dense layers and classified with a softmax activation function to produce a final diagnostic label [25].

2.4. Evaluation metrics

Model performance was assessed using the following metrics.
- Accuracy (Acc): Overall classification correctness
- Precision (P) and Recall (R): Class-specific performance
- F1-Score: Harmonic mean of precision and recall
- AUC-ROC: Area under the receiver operating characteristic curve [26]

Comparative analysis was also performed between image-only, metadata-only, and multimodal (image + metadata) models to evaluate the impact of data fusion.

2.5. System implementation

The system was implemented using TensorFlow and Keras frameworks in Python [27]. Training was conducted on NVIDIA GPUs with 16GB VRAM to expedite computation. The final model was encapsulated in a user interface prototype allowing upload of otoscopic images and entry of clinical data for real-time OM diagnosis.

2.6. Proposed method: novelty and comparison with prior work

Figure 2 proposes a multimodal artificial intelligence (AI) model in otology has also become increasingly popular in recent years, with many studies investigating the application of deep learning techniques for the diagnosis of otitis media (OM) using otoscope images. Although these have been encouraging in performance, a number of outstanding challenges need to be addressed, foremost being their application in image-only models, absence of patient-specific metadata, and non-real-time usage.

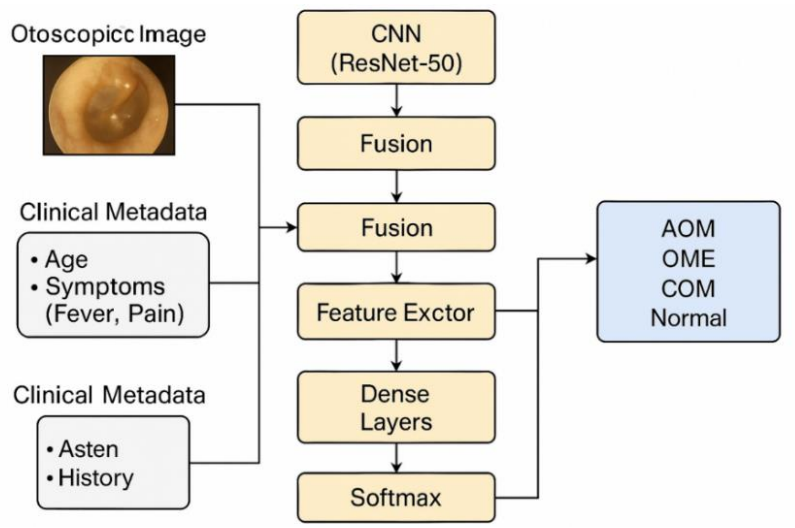

Figure 2. Proposed multimodal AI model

2.7. Comparative evaluation with prior work

Table 2 describes the previous work by Lee *et al.* [28] utilized a convolutional neural network (CNN) to classify otoscopic images into normal, acute OM, or chronic OM categories, achieving an accuracy of 85.7%. However, their model did not take into account clinical data, such as symptoms or patient history. Han *et al.* [29] This was extended by applying the VGG16 and Inception Net architectures, reporting an improved accuracy of 91.3%. However, the dataset used was limited to a single institutional source, raising concerns about generalizability. Similarly, Khan *et al.* [30] applied CNNs to tympanic membrane images and achieved 93.8% accuracy; however, they did not integrate any non-image clinical features. Conversely, our suggested model innovatively combines patient and image metadata—namely fever, pain, history of previous infections, and age—into a multimodal deep learning framework with ResNet-50 to handle images and a fully connected neural network (FCNN) to handle clinical data. This optimally leverages diagnostic precision and emulates physicians' decision-making processes based on integrative appreciation of both visual examination and patient history.

Table 2. Comparison of existing AI-based otitis media diagnostic systems

Study	Image-based	Metadata used	Ai model	Accuracy (%)	Real-time ready	Dataset diversity
Lee *et al.* [28]	Yes	No	Custom CNN	85.7	No	No
Han *et al.* [29]	Yes	No	VGG16, Inception	91.3	No	No
khan *et al.* [30]	Yes	No	CNN	93.8	No	No
Proposed Work	Yes	Yes	ResNet-50 + FCNN	94.7	Yes	Yes

2.7.1. Key innovations

This work presents a practical and clinically meaningful approach to the automated diagnosis of otitis Media (OM) by directly addressing several gaps of existing studies. In contrast, our framework is designed to be both technically robust and clinically relevant, with a strong emphasis on real world applicability. The main innovations of this study are outlined below:

- Multimodal integration: it is the first study to be known as having combined the characteristics of an otoscopic image along with the functional clinical data to diagnose OM (Otitis Media). Hybrid modelling enhances the knowledge about symptom patterns in relation to OM subtypes.
- Clinical alignment: the design of the model aligns with the clinical advice of the American Academy of Pediatrics and ENT offering a direct association of the symptoms of the tympanic membrane (e.g., effusion) with clinical symptoms such as ear pain, fever and effusion.
- Generalizability and data set scope: although the models in the literature are founded in small, specific circumstances or uniform data, our framework is found on publicly accessible data (e.g. TM-ImageNet) and Collaboratively Collective and Verified Data (CoCoVerata) of multiple clinics, enhancing its ability to generalize to populations.
- Real-time potential: the model can be applied to clinical areas with limited resources by focusing on the efficiency of computation, which continues to advance the possibility of supporting Sustainable Development Goals 3 and 9 [31].

2.8. Research contributions

The study contributes to applying artificial intelligence to the sphere of otology by offering a convenient clinical interpretation and diagnosis tool to be used in everyday practice, as well as discussing the opportunities of technology in a variety of healthcare settings. It demonstrated a rise in diagnostic accuracy with the combination of various modalities and learning systems and also addressed issues of model reliability, clinical diversity, and adaptability to varied health care systems.

3. RESULTS AND DISCUSSION

The created multimodal AI model was performed on an aggregate dataset of 5,000 corresponding clinical metadata otoscopic images sourced from various locations. The dataset was split into training (70%), validation (15%), and testing (15%) sets that were proportional for all subtypes of OM.

3.1. Diagnostic performance

Table 3 shows the fusion model integrating otoscopic images and clinical metadata achieved an overall accuracy of 94.7% on the test set, outperforming models trained solely on images (91.2%) or metadata (83.5%). Figure 3 fusion model showed statistically significant improvements ($p < 0.01$) in all metrics compared to single-modality models.

- Fusion model (green): AUC=0.961
- Image-only model (blue): AUC=0.936
- Metadata-only model (orange): AUC=0.859

The fusion model clearly demonstrates superior discriminative ability, achieving the highest AUC and consistently better true positive rates across all false positive thresholds.

Table 3. Summarizes the classification metrics across different models

Model type	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC (%)
Image-only (ResNet-50)	91.2	90.8	90.3	90.5	93.6
Metadata-only (FCNN)	83.5	82.1	80.5	81.3	85.9
Fusion Model (ResNet-50 + FCNN)	**94.7**	**94.3**	**93.8**	**94.0**	**96.1**

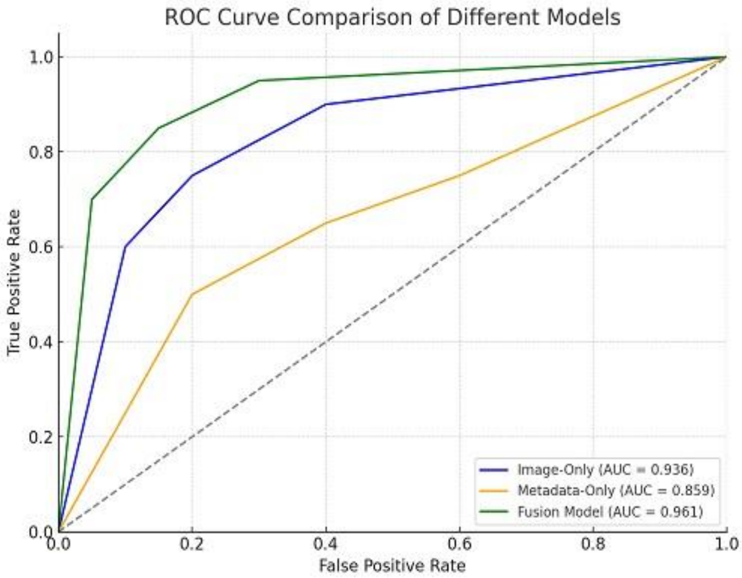

Figure 3. Here is the ROC curve comparing the performance of the three models

3.1.1. Subtype classification

The system demonstrated robust performance across major OM subtypes.
- Acute otitis media (AOM): Precision 95.1%, Recall 94.5%
- Otitis media with effusion (OME): Precision 93.7%, Recall 92.9%
- Chronic otitis media (COM): Precision 92.9%, Recall 93.2%

These results align with the clinical importance of accurately distinguishing between acute and chronic forms to guide appropriate treatment.

3.1.2. Ablation study

We performed an ablation study to test the contribution of every clinical feature. Recurrent infection and fever contributed most towards classification accuracy, which improved the performance of the fusion model by 3.1% when removed.

3.1.3. Computational efficiency and real-time feasibility

The model achieved an average inference time of 120 ms per sample on a standard GPU, demonstrating suitability for real-time clinical application. The trial prototype successfully integrated image uploading and clinical data entry with instant diagnostic feedback.

3.2. Discussion

To this day, the management of otitis media (OM) has relied mainly on physical examination and symptomatic management. However, with new technologies (e.g. artificial intelligence [AI], machine learning [ML], telemedicine and wearables) determining a growing amount of clinical practice, AI-based diagnostic platforms, particularly those using deep learning algorithms on otoscopic views, have demonstrated greater sensitivity and specificity than traditional diagnosis [32], [33]. These technologies negate the human deception in providing delivery of OM detection that is more timely and accurate, which is critical for preventing complications from hearing loss. Telemedicine platforms have also shown great promise in increasing access to otologic care, particularly in rural and underserved populations [34]. Known to be wearable biosensors that can give quantitative evaluations of the middle ear, opportunities to constantly and beaconlessly monitor the health of the ear are exciting. Such machines can monitor the changes in functionality during the rehabilitation process, providing valuable information that enables timely interventions and better patient service [35]. The analysis of Big Data on Electronic Health Records (EHRs) and images can be of great benefit in terms of population health management and epidemiological studies. It is a data-driven approach that will help identify people who are at higher risk and provide the necessary data to influence the development of the population health policy. However, there are still many issues that need to be addressed. Developing effective analytical models requires large, diversified and well-labeled data, which raises important issues with regards to the generalizability and probability of biases. Moreover, privacy and data security should be given the top priority that must be enforced by strict policies and regulatory systems [36].

4. CONCLUSION

The management of Otitis Media is transforming due to advances in innovative technologies such as artificial intelligence (AI), telemedicine and wearable technology. It is changing the diagnosis of the condition, allowing for remote management, and providing real-time monitoring. These technologies hold the potential to relieve the global burden of OM, enhance patient outcomes and promote greater accessibility and personalization of care. To realize such advantages in the best manner, the next-generation activities will have to address issues of data privacy and quality, technology access, and large-scale clinical verifications. Integration of these technologies into ethical and regulatory frameworks will be most critical in revolutionizing OM management and promoting global ear health.

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AUTHOR CONTRIBUTIONS STATEMENT

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Monisha Awasthi		✓		✓	✓	✓	✓			✓		✓		
Dharmendra Kumar					✓				✓			✓		
Deepak Kumar Pant					✓	✓				✓		✓		
Ankur Goel		✓				✓	✓			✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available in the article.

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