Automating Otoscopy: Meta-Analysis of Artificial Intelligence to Diagnose Ear Disease from Otoscopic Images

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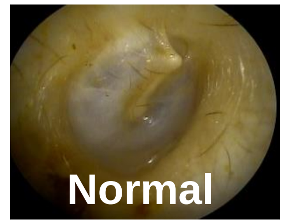
Background and Rationale

Access to otolaryngologists is limited in rural and remote areas, where most ear disease screening is performed by community health nurses. Artificial intelligence (AI) using machine learning and neural networks has the potential to support untrained health workers triage ear disease from otoscopic images.

Our objective was to determine the accuracy of AI to diagnose ear disease from otoscopic images.

Step 1
Humans label training data



Step 2
Algorithm generates inferred function

$$f(x) = \begin{Bmatrix} normal \\ abnormal \end{Bmatrix}$$

Step 3
Computer uses function to label new data

$\xrightarrow{f(x)}$

Methods

A literature search was conducted of MEDLINE, EMBASE, Pubmed and Google Scholar databases, for articles that a) used otoscopic eardrum images, b) applied machine learning or convolutional neural networks, and c) used primary care practitioners or otolaryngologists as the ground-truth (gold standard). Ear disease categories: normal, acute otitis media (AOM), otitis media with effusion (OME), perforation, wax impaction and tympanosclerosis (TS).

Results

Nine of 1,544 articles were included, comprised of 13,398 otoscopic images (12,541 used for training/validation and 857 used for testing).

Table 1. Characteristics, methods and outcome measures of included studies.
Abbreviations: multitask joint sparse representation based classification (MTJSRC), support vector machines (SVM)

Author (year)	Diagnoses	ML / CNN	Ground-truth
Cha (2019)[1]	normal, perforation, TS, wax	Inception V3, ResNet	Otolaryngologist
Livingstone (2019)[2]	normal, perforation, AOM, OME, wax,	Google Cloud Vision	Otolaryngologist
Senaras (2019)[3]	abnormal	Inception V3	Otolaryngologist
Seok (2019)[4]	normal, perforation	ResNet	Otolaryngologist
Kasher (2018)[5]	AOM	Inception V3, MobileNets	Primary care practitioner
Tran (2018)[6]	AOM, OME	MTJSRC	Otolaryngologist
Myburgh (2016)[7]	normal, AOM, OME, wax	Matlab	Otolaryngologist
Shie (2014)[8]	OME	Adaboost	Otolaryngologist
Mironica (2011)[9]	AOM, normal	SVM	Otolaryngologist

Table 2. Meta-analysis of diagnostic accuracies for common clinical findings..

Diagnosis	No. of studies	Accuracy (95%CI)
Normal	5	87.7% (84.8 – 90.3%)
AOM	5	85.5% (82.5 – 88.1%)
OME	4	88.7% (85.2 – 91.6%)
Perforation	3	85.1% (80.4 – 89.1%)
Wax	3	84.4% (78.5 – 89.3%)

Discussion

Current research demonstrates that AI can accurately interpret otoscopic images comparable to clinicians. The possibility of harnessing this technology to improve safety and efficiency, and to anticipate needs of care in rural and remote areas is promising. However, these methods require rigorous evaluation and replication before widespread adoption into clinical practice. Future applications may include point-of-care tools to enable community health workers triage eardrums instantaneously and initiate specialist referral for high-risk patients.

References

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