WESTMEAD ENT

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Artificial intelligence to classify ear disease and predict hearing loss in Aboriginal and Torres Strait Islander children from rural and remote areas

Project website: www.drumbeat.ai

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Acknowledgement of Country

We acknowledge the traditional owners of the land on which this research was conducted, there spiritual relationship to the land, and their elders past, present, and emerging.

Introduction

Ear disease is a major public health issue for Aboriginal and Torres Strait Islander people.[1] Long-term hearing loss in childhood can impact speech and language development, academic performance, behaviour, social isolation, future employment opportunities, and contribute to increased contact with the criminal justice system.[2]

Indigenous children are three times more likely to have ear disease and twice as likely to have long-term hearing loss than non-Indigenous children in Australia.[3] The burden of ear disease is greatest for Indigenous children living in rural and remote areas, as these children are twice as likely to experience long-term hearing loss than non-remote Indigenous children.[3] Access to Ear, Nose and throat (ENT) specialists and audiologists is limited in rural and remote areas.[4] Most ear health screening is performed by nurses or community health workers (HWs) in primary care who collect eardrum photos using otoscopic cameras.[5] However, HWs are often less experienced than ENT specialists to accurately interpret eardrum photos and diagnose ear disease.

Advances in modern computing and artificial intelligence (AI) may provide a novel approach to overcome delays in diagnosis and improve the triage of high-risk children. Machine learning (ML) is a fundamental component of AI, allowing computers to learn by recognising patterns to make predictions.[6] Convolutional neural networks (CNNs) are ML techniques that have been used to develop computer vision algorithms for clinical practice, such as for detecting diabetic retinopathy and evaluating skin lesions.[7,8]

Augmenting current ear disease screening programs with AI may assist frontline HWs to triage ear disease with increased accuracy, efficiency, and confidence. Early detection of ear disease may support early treatment and referral, to minimise the risk of long-term hearing loss.

Purpose

To develop an AI-based algorithm for otoscopy to classify and ear disease and predict hearing loss for Aboriginal and Torres Strait Islander children living in rural and remote areas.

Aims

1. Summarise Australian telehealth otoscopy databases collected from rural and remote areas, and evaluate inter-rater agreement of diagnostic labels (i.e. ground-truth)
2. Develop an AI-otoscopy algorithm to classify ear disease, using otoscopic images from Aboriginal and Torres Strait Islander children
3. Compare performance between experts and an AI-based otoscopy algorithm to classify ear disease
4. Develop an AI-otoscopy algorithm to predict likelihood of conductive hearing loss (CHL) using otoscopic images

Funding sources

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Methods

Ethics

Menzies School of Health Research (HREC: 2019-3410)
Children's Health Queensland (HREC: 20/CHQ/68498)

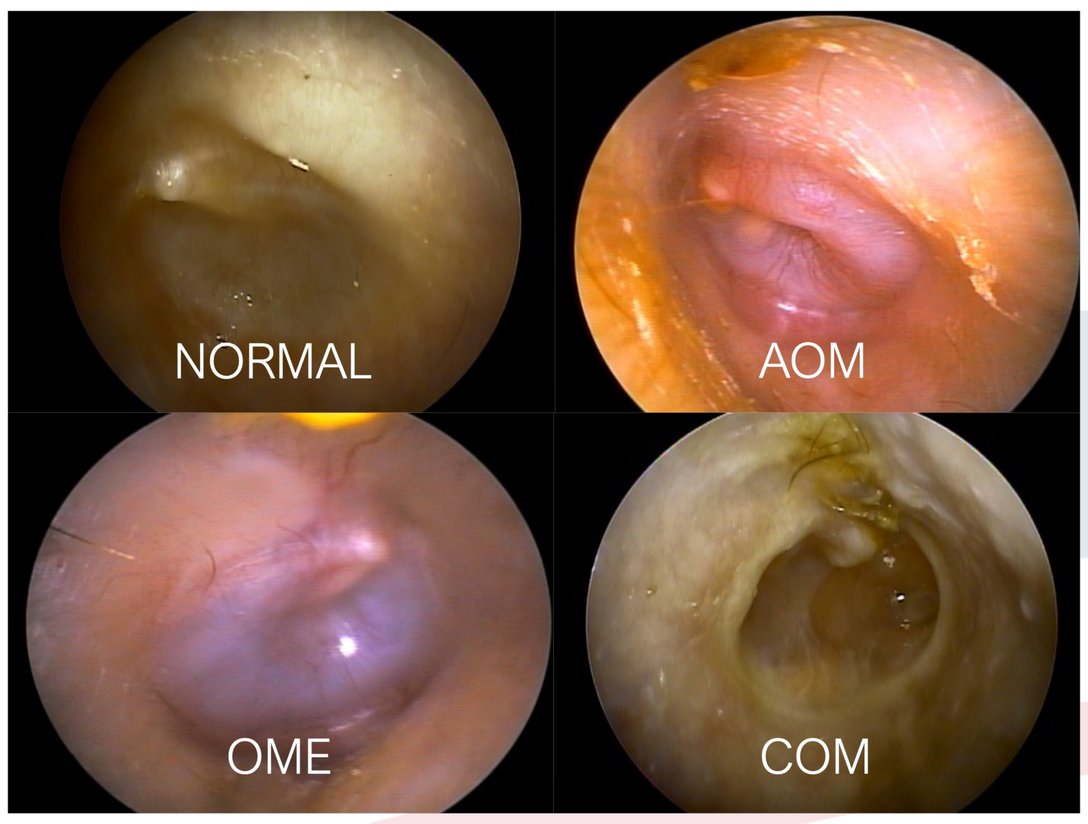
Data sources (Telehealth programs)

1. Royal Darwin Hospital, NT, Australia (2011 – 2019)
2. Deadly Ears Program, Qld, Australia (2017 – 2020)

Ear assessments

Otoscopy performed by specialty trained nurses as per standard of care for telehealth programs. Hearing assessments performed by audiologists. Clinical data reviewed asynchronously by otolaryngologists to establish ear disease diagnosis (i.e. ground-truth).

Diagnostic categories of interest



Legend: AOM – acute otitis media, OME – otitis media with effusion, COM – chronic otitis media

Deep learning architecture

Image classification algorithm developed with pre-trained CNN (ResNet-152) via transfer learning.

Training images

- Model 1 (ear disease category): n=9086
- Model 2 (hearing loss): n=4457

Outcomes

- Accuracy
- Agreement (prevalence-bias adjusted κ scores)

Results

Table 1. Summary of Australian teleaheatlh otoscopy databases

	Royal Darwin Hospital (NT)	Deadly Ears Program (QLD)
Patients (n)	3950	639
Mean age (years)	11.9 ± 5.1	6.5 ± 3.4
Females, Males	53%, 47%	47%, 53%
Diagnostic categories		
Normal	37%	59%
AOM	3%	4%
OME	17%	18%
COM	34%	19%

Table 2. Inter-rater agreement between 13 otolaryngologists to diagnose otitis media in Aboriginal and Torres Strait Islander children using a telehealth approach

	Accuracy (%)	Adjusted κ
Tier A	65% (95%CI: 63 – 68%)	0.53 (95%CI: 0.48 – 0.57)
Tier B	77% (95%CI: 74 to 79%)	0.68 (95%CI: 0.65 – 0.72)
Tier C	85% (95%CI: 82 – 87%)	0.79 (95%CI: 0.76 – 0.82

Legend: Agreement – proportion of agreement between raters and reference standard, Adjusted κ – prevalence-and-bias-adjusted linearly weighted.
Tier A - Otoscopic images only.
Tier B - Otoscopic images with tympanogram type and category of hearing loss.
Tier C - Otoscopic images with tympanometry (tympanogram type, static compliance, middle ear pressure, ear canal volume), pure-tone audiograms and nurse impressions (otoscopy findings and presumed diagnosis).

Table 3. Summary of performance between experts and AI-otoscopy algorithm to classify ear disease

	13 Experts *(using otoscopy, audiometry and clinical notes)*	Algorithm *(using otoscopy only)*
Overall	85% (95%CI: 82 – 87%	88% (95%CI: 81 – 96%)
Subtype		
Normal	93%	100%
AOM	69%	100%
OME	78%	71%
COM	89%	88%

Table 4. Performance of AI-otoscopy algorithm to predict likelihood of conductive hearing loss (CHL) using otoscopic images

	CHL (Accuracy)	*No CHL (Accuracy)*
Overall	85%	93%
Subtype		
Normal	-	95%
AOM	87%	100%
OME	76%	100%
COM	93%	100%

Discussion

Aboriginal and Torres Strait Islander children living in rural and remote areas have limited access to otology and audiology services, contributing to wait times that exceed established recommendations. Telehealth has been used as an alternative model of care to provide ear health services through community partnerships. In-field examinations performed by HWs and interpretations provided by specialists are asynchronous, representing delays to establish diagnoses, potential increased risks for adverse complications, and loss to follow up.

Using otoscopic images alone, an AI-based otoscopy algorithm achieved comparable performance to classify ear disease relative to experts reviewing otoscopy, audiometry and clinical findings documented by in-field HWs. The algorithm was more likely to classify AOM and normal ears, but less likely to classify OME and COM. The disposition and history of children during ear examinations are important aspects to achieve accurate diagnoses and management plans. Under recognising AOM during initial in-field, point-of-contact assessments may have downstream impact on the final diagnosis established by experts using a telehealth model of care. Differentiating OME from AOM is challenging and often requires consideration of tympanometry and audiometry. The performance achieved by the algorithm may improve if considering the addition of audiometry and symptomatology.

The AI-otoscopy algorithm achieved substantial performance to identify the presence or absence of CHL using otoscopic images alone. In settings where audiologists services are limited, an AI-supported clinical tool may assist HWs triage children with CHL for specialist review. Early recognition of CHL is important to minimise the detrimental impact of long-term impact on childhood development.

Conclusion

AI has the potential to augment otoscopy to enhance the capacity of HWs in rural and remote areas recognise and triage ear disease. AI-based tools could be used to flag cases that are diagnostically uncertain or screen through normal images to rapidly identify concerning pathology and recommend treatment or surveillance. Further refinement, validation, and in-field assessment is required.

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