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A Review On Machine Learning Assessment Of Hearing Loss

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Abstract

This study's goal is to give a summary of digital methods for automated hearing loss estimation utilizing pure tone audiometry, with a particular emphasis on issues of accuracy, dependability, and timeliness. This study aims to provide a comprehensive analysis of the 2013 systematic review and make it useful to a larger audience. By 2050, it is expected that 25% of the world's population would have hearing impairment, up from the current 20% prevalence. As therapy depends on a correct diagnosis of hearing loss, this first step is out of reach for more than 80% of those who are affected. For the purpose of evaluating the commonalities between the various research, significant information regarding the purpose and specifics of each report was gathered. Their reports from numerous studies conducted between 2012 and June 2021 were included. Numerous distinctive automated methods were found from this selection. In comparison to conventional range-obtaining methods, machine learning algorithms require fewer trials, and individualized digital tools make assessment more affordable and available. Using digital approaches for quality monitoring, such as noise monitoring and result inconclusiveness detection, can improve validity. A growing variety of automated methods have demonstrated accuracy, dependability, and time effectiveness comparable to manual hearing evaluations over the last ten years. Beyond human audiometry, new developments—including methods for machine learning—offer features, cost-effectiveness, and variety. When carried out according to predetermined guidelines, automated evaluation using digital technologies can facilitate work-shifting, self-care, telehealth, and clinical treatment options.

1. Introduction

Around the world, 1.5 billion people suffer from hearing loss, and that number is projected to rise to 2 billion by 2050 [1]. The first step toward suitable and prompt therapy is a hearing test. Due to the fact that there is less than one hearing health expert for every million individuals in places like Africa, the majority of people who are impacted by hearing loss are unable to get hearing examinations [2]. In order to give self-administered hearing exams, more automated approaches (all components of the procedure related with automated audiometry), including machine learning, are being developed. Automated audiometry refers to any hearing test that a patient administers himself right away. We define automated audiometry in this review as pure-tone audiometry that is self-monitored from the start of the test in any situation (e.g., workplace health, hearing healthcare, and community centres).

Model-based methods that learn from data of real examples as opposed to rules are referred to as machine learning. Automated techniques provide health care paths with the potential to improve accessibility, efficiency, and scalability because professional input is not necessary. As the direct involvement of professionals is not required, automated approaches enable health care pathways with the potential to increase accessibility, efficiency, and scalability. Digital (health) technologies, including apps, smartphones, tablets, and wearables, can acquire data remotely; expand the reach and precision of clinicians; and facilitate more personalized hearing health care within a network of distributed expertise [3]. Recent examples of automated hearing assessments include clinical grade and consumer-grade applications [4].

General global health trends suggest that increased availability of diagnostic tools could lower health care costs and improve quality of life. In tuberculosis screening in low-resource settings, an automated diagnosis can increase the sensitivity of identifying persons at risk while reducing costs [5]. For example, in Parkinson disease, remote care based on wearables provides ecologically valid methods for monitoring and evaluating symptoms [6]. Self-assessment using eHealth vision tools improves access to diagnosis and facilitates timely diagnosis.

Early detection and treatment of hearing loss are critical for achieving optimal outcomes and quality of life throughout life. Untreated hearing loss limits children's language development and educational potential and is linked to a faster cognitive decline in adults [7]. It may result in social isolation, lower socioeconomic status, increased social disparities, and decreased health, resulting in lower individual quality of life and significant community costs [8]. Importantly, treating hearing loss in middle age has been identified as the most significant potentially modifiable risk factor for dementia later in life [9]. The capacity of the entire clinical pathway should be increased because a bottleneck is looming if access to diagnosis increases faster than access to affordable treatment and rehabilitation.

Automated self-testing options are critical for detecting and diagnosing hearing loss in order to direct timely and appropriate treatments. The vast majority of treatments are for permanent age-related and noise-induced hearing loss, but a sizable portion of the population requires medical treatment for hearing loss. The emergence of the COVID-19 pandemic has highlighted the importance of self-testing approaches [10]. Automation on digital devices is a powerful enabler of alternative diagnostic pathways, such as home-based testing, low-touch service models outside of traditional clinic settings, and decentralised community-based models based on task shifting to minimally trained facilitators [11].

2. Literature Review

By focusing on accuracy, reliability, and efficiency, we carried out a comprehensive scoping analysis of the practitioner literature on automated and machine learning methodologies to validate pure-tone threshold audiometry utilising digital technology. Several studies have produced hearing loss methods or strategies that can improve or simplify the work of otolaryngology practitioners. The K-mean technique is used to apply cluster forms of audiograms in homogeneous and inhomogeneous clusters to aid physicians in the diagnosis of hearing loss [12]. Pure tone data from 1633 people were used in their study. The K-means clustering method divided the audiogram format into several cluster numbers, including 4, 5, 6, 7, 8, 9, 10, and 11. The clusters were assessed using ANOVA, which was then used to test the hypothesis that the various audiogram styles are homogeneous. According to the study's authors, a clinician's diagnosis is dependent on their own subjective observations, which are not always accurate. In addition, an audiogram classification system that is consistent is required in order to help clinicians make diagnoses. In respect to the classification of these audiograms, the researchers did not identify any pathologies, symptoms, or frequency. The connection between different audiogram types and specific patient features can be understood by specialists thanks to this association.

A decision-support system for the assessment of hearing loss symptoms has been developed by Moein et al. [13]. 150 patients from an otolaryngology clinic were included in their study. Serous otitis media, otitis media, conductive fixation, cochlear age, cochlear noise, and normal hearing loss symptoms were divided into six classes using the Multi-Layer Perceptron Neural Network (MLP) and Support Vector Machine (SVM).

To further improve in the identification of vertigo and hearing loss symptoms, [19] developed the Otoneurological System. The researchers concentrated on testing the mechanism of nearest K and Naive Bayes classification techniques to evaluate the accuracy of machine learning techniques and the accuracy of classification, the combination of the knowledge learned from machine learning techniques with domain-specific knowledge to obtain information from patient data that will aid in diagnosis. 815 experimental cases made up an otoneurological dataset that was gathered. The gathering of the data reveals acoustic neurinoma, Meniere's disease, benign positional vertigo, abrupt deafness, traumatic vertigo, and vestibular neuritis. In order to assess the precision of these predictions, the researchers added an additional 1030 vertigo cases to a dataset obtained from the Helsinki University Central Hospital. Two vertigo datasets were employed in the study's knowledge exploration technique, and results were compared to those of an otolaryngologist. The classification accuracy is frequently integrated in various ways to evaluate the impact of both the otolaryngology information and the outcomes of the machine learning technology. When professional knowledge and knowledge from otolaryngologists were combined, the results demonstrated the highest accuracy of classification. The system was designed exclusively for diagnosing vertigo symptoms, and evaluating the dataset system that only contains vertigo instances received additional attention. Another flaw in this experiment was how the predicted accuracy of the data obtained from the learning approach was estimated. Only 30% of instances were used for testing and 70% were used to train algorithms [14]. In order to improve the detection of tinnitus, the interpretation of results, and an overall understanding, Thompson et al. [15] employed a medical records database to find information on the causes and treatments of tinnitus. Additionally, it was via this study that a strategy for identifying just one sign of hearing loss was discovered.

By using an online resource to play a variety of tones at different volumes to the users, who will then be asked to choose the specific tones they can hear, the diagnostic model for the diagnosis of vestibular schwannomas from audiometric data has been established and validated [16]. They will receive a summary of the findings to review in AudioGen, a technique that uses machine learning techniques to identify the genetic basis of hearing loss in individuals segregating autosomal prevalent non-individual hearing loss using phenotypical information generated from audiogram data. The article's findings demonstrate the causal gene's predictability within the three top predictions, with an algorithmic accuracy of 68%. A prediction accuracy of 68% is a level of precision that needs to be implemented with caution in the healthcare industry [17], despite the fact that AudioGene is a step forward in this regard because of the tremendous relevance of knowing the genetic aetiology of hearing loss.

By using machine learning approaches, Bing et al. [18] established a predictive model for the hearing result in unexpected sensorineural hearing loss. The SSHL may be a complex disease with significant heterogeneity, which would explain why the findings vary greatly. Through the use of four machine learning techniques, their research helped to develop predictive models for SSHL that identified the best performer for clinical use. To identify the dichotomized hearing result of SSHL by adding six features gathered from 149 potential indications, the deep learning method has been utilised with support vector machines, logistic regression, and neural networks. The execution of the different approaches' predictive capabilities were compared using the metrics of precision, accuracy, review, F-score, recall, and ROC curve. In general, the DBN technique demonstrated outstanding predictive performance when tested on the 149-factor crude information set, achieving an accuracy of 77.58% and an AUC of 0.84. Further, Shew and Staecker [19] developed disease-specific algorithms using machine learning to predict varying levels of SNHL in a variety of internal ear disorders based solely on a perilymph-derived miRNA expression profile. Patients whose internal ears were opened as part of the cochlear implantation and stapedectomy procedure provided 2–5 L of perilymph, which was collected. Then, they used a directed machine learning classification to assess the miRNA dataset specific to internal ear disorders, displaying and taking into account multiple-choice models such as multiclass decision forests, decision jungles, computed relapse, and neural systems. They built the demonstration using a 70/30 split, using 70% of the patients for construction and the remaining 30% for testing the ML demonstration. It is possible to determine which component was used and at what weighted esteem throughout the ML step of emphasising the significant components.

Many automated testing procedures for hearing loss have been suggested in the related literature by numerous investigations [20,21]. The primary objective of the associated research was to accurately analyse the hearing impairment by lowering the absolute error rate and maximising precision. The procedure is limited to air conduction audiometry, though, and as a result, a complete evaluation of the patient is impossible without using additional testing modalities like bone conduction and conversation audiometry. The large numbers of the automated methods previously mentioned are known to have problems like inaccurate results at lower frequencies, background noise, difficulty identifying conductive and sensorineural hearing losses, decreased precision and effectiveness due to the absence of discourse audiometry, etc. By suggesting a model of symptom detection to precisely categorise hearing loss symptoms based on pure audiometry data from air and bone conduction, this work presents a significant possibility to improve the diagnostic process of hearing loss symptoms. The model is adopted using FP-Growth and NB, where NB models are supervised models employed for the classification aim while FP-Growth is an unsupervised method used for feature extraction. For this, FP-Growth was first used to examine the link between hearing thresholds and hearing loss symptoms using small sample and large sample datasets.

Based on a strategy for extracting features and identifying discourse that was cognitively motivated, Nisar et al. [20] introduced a new model that automatically recognises hearing impedance. In their suggested method, the client is asked to repeat the machine's spoken phrases. Client response is first detected through the discourse signal, and the framework recognises accurate and incorrect hypotheses made by the client in order to naturally produce an audiogram and discourse identification limit. Finally, a number of machine learning-based classification techniques, such as the Hidden Markov Model (HMM), k-NN, SVM, and AdaBoost, were applied. To achieve a precision of up to 96.67% using the Hidden Markov model, the big absolute error of the suggested approach is often less than 4.9 dB and 4.4 dB for the pure tone and conversation audiometry testing, respectively, when compared to the professional audiologist testing. Given the lack of comprehensive databases, Cárdenas et al. [21] also demonstrated a machine learning application to discriminate and categorise hearing loss cases based on feature extraction from artificially manufactured brainstem sound-related evoked possibilities. The approach is predicated on a multi-layer perceptron, which has proven to be a useful and efficient tool in this area. Preparatory results seem to be quite helpful, with accuracy rates above 90% for a variety of hearing loss problems; this framework is to be conveyed as equipment performance for creating an affordable and practical treatment device, as described in earlier studies.

3. Discussion and conclusion

For successful adoption, standardized measures of accuracy, reliability, and efficiency are needed for comparative purposes. Certification and independent reviews may help prospective users select trustworthy approaches. Further reliability can be achieved by determining which difficult-to-test populations may not be appropriate for automated testing and how to detect and then triage these patients to specialized centres. Further contextual information, such as standardized metadata, is needed to help clinicians interpret the context and limitations of test outcomes. If researchers and clinicians deal carefully with their limitations, automated hearing assessments can be designed such that they form an effective part of service delivery for many people who have or are at risk of hearing loss. Automated audiometry can be part of existing caring directions and also enable new service models, including task shifting to community health workers delivering decentralized care, virtual hearing health care, and over-the-counter or direct-to-consumer hearing aid dispensing. Fully adaptive procedures, including machine learning techniques, seek hearing thresholds more efficiently. Inexpensive digital devices such as smartphones can be turned into audiometers, increasing accessibility and availability. Higher reliability is achievable by signalling invalid test conditions, and child-friendly user interfaces offer a solution to the hard-to-test population. These approaches can be implemented in the clinical care pathway, remote or virtual hearing health care, community-based services, and occupational health care to address the global need for accessible hearing loss diagnosis. To provide a better efficiency of the machine learning approaches, the dataset samples in future work must be increased. It is assumed that a machine learning algorithm would produce classification or prediction results that are more reliable the more training sets and validation data it has access to. It is also advised to employ deep learning techniques to get a higher accuracy and training process.

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