EEG Based Classification of Normal And Abnormal Hearing Using Elman Neural Network

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Abstract- *An electroencephalogram (EEG) is the best tool to determine hearing level for people who lack verbal communication and a behavioural reaction to sound stimuli. Auditory evoked potentials (AEPs) are a form of EEG signal that is sent from the brain's scalp in response to an auditory stimulus. The significance of a standard hearing screening test is constrained since it requires a response from the test subject. The main goal of this project is to create an intelligent hearing ability level assessment system employing auditory evoked potential signals in order to address this issues. A simple method is proposed in this research to classify a subject's hearing level using Elman neural network. Early detection of this illness can help to reduce the severity of the illness. AEP signals from ten normal and ten impaired hearing patients were recorded unilaterally with a monaural auditory stimulus, and a link between brain dynamics and hearing threshold response was discovered. Independent power spectral feature and spectral entropy feature are derived from the recorded AEP signals. To link features with normal and abnormal hearing levels, a gradient descent backpropagation with adaptive learning rate algorithmis applied to the Elman neural network. The neural network model has a maximum classification accuracy of 92.75 in distinguishing between normal and impaired hearing people for the left and right ears.*

Keywords- Auditory Evoked Potential, EEG, Hearing Threshold, Neural Networks

I. INTRODUCTION

The most common sensory impairment in the world is hearing loss.A hearing loss is a partial or complete loss of hearing. Hearing loss can be a lifelong condition or progress gradually, which is often brought on by genetic or prenatal factors as well as infections that harm the auditory pathways.There are more than 275 million hearing-impaired people in the world. 0.5 percent of the newborn have the hearing disorder. Data from the INEGI national census of demographic dynamics show that 7.2 million people, or 6% of the population, have a disability, with auditory impairments accounting for 33.5% of those disabilities. Difficulty to speak, disturbances while communicating, delayed language comprehension, academic disadvantage, lack of job opportunities, social isolation are all effects of hearing loss. Effects of hearing loss also include stuttering, trouble understanding speech, especially when there is background noise, frequently requesting others to speak louder, retreat from conversations, and avoidance of certain social situations. Emotional issues are brought on by a drop in confidence and self-worth. Damage to the inner ear, gradual earwax buildup, ear infections, abnormal bone growths or tumors, and ruptured eardrums are all causes of hearing loss. Common causes of hearing loss include ageing, loud noise, hereditary factors, occupational noises, recreational noises, some drugs, and certain illnesses. One of the best approaches to handle this issue is to perform an early hearing screening test using an electroencephalogram (EEG). A technique that is frequently used to detect neurological disorders and problems with brain dynamics is electroencephalography[3]. When an auditory stimulus is applied to the brain's scalp, an EEG signal known as an Auditory Evoked Potential (AEP) is generated. Hearing threshold values are assessed using the AEP response. The AEP signal is made up of repeatable positive or negative peaks, latency, amplitude, and behavioral correlation. In comparison to EEG signals, AEPs have a substantially lower amplitude. The amount of auditory capacity of a person is reflected in the AEP response. Machine learning algorithms that recognize and categories patterns have been developed using approaches from these fields[7]. A simple hearing threshold level technique based on AEP signals is proposed in this research to identify a person's hearing threshold level. The AEP signals were stimulated at the hearing frequency level 1000 Hz and at a fixed sound intensity level of 25 dB in the experimental study, and the matching hearing threshold level was unilaterally recorded using monaural acoustical stimulation. AEP signals recorded from normal and abnormal hearing people are used to derive spectral information. To distinguish normal and abnormal hearing levels, Elman neural network model is designed and applied.

II. RELATED WORKS

In this section, we briefly describe multiple studies related to this work, and it is clear that the majority of the researchers used a two-channel EEG data collecting equipment. As part of a classification method for the hearing threshold, auditory evoked potential signals were generated using feed forward neural networks with backpropagation algorithms[1]. After gathering two different kinds of AEP signals, the acquired feature sets were classified using the K-Nearest Neighbors algorithm [2]. Using the Autoregressive (AR) pole tracking technique, which keeps track of the position of the poles, the upper and lower hearing threshold components of an individual were retrieved [3]. The Levenberg-Marquardt algorithm (LM) and a multilayer feed forward neural network are used in clinics to produce final results for calculating a person's threshold level[4]. Event-related spectral perturbations (ERSPs) in the alpha and beta ranges were computed for the two conditions at central electrode sites overlying the sensorimotor cortex were discussed [5] in a computational model that uses both spatial and temporal information has been manifested in EEG signals for auditory spatial attention detection (ASAD) [6]. AEP signals, which represent auditory evoked potentials, have been proposed as a way for calculating hearing ability [7]. Neetha Das and Tom Francart have described an EEG-based auditory attention detection (AAD) paradigm with an acoustic noise reduction algorithm based on the multi-channel Wiener filter (MWF), leading to a neuro-steered MWF in their papers [8]. In the setting of both neural and ocular artefact sensitivity, the findings from these papers can be used to support both ongoing and upcoming experimental ear-EEG studies and applications [9]. Participants with hearing loss have a larger gamma band power value than individuals with normal hearing, according to Kamalraj Subramaniam's research [10].

III. MATERIALS AND METHOD

A. EEG Recordings and Data Acquisition:

An electroencephalogram (EEG) is a test that uses tiny, metal discs (electrodes) connected to the scalp to assess electrical activity of the brain. Electrical impulses are the primary means of communication among brain cells, which are always active even when sleeping. On an EEG recording, waves can be seen during this activity. An EEG can spot variations in brain activity that may help with diagnosing mental problems. Twenty persons in total participated in the study. The normal hearing group (NHG) and the abnormal hearing group (AHG) were the two distinct groups of participants in this study. Ten participants with normal hearing made up the NHG (NHG consists of men; age: 24.4 +- 3.5 years), whereas ten participants with abnormal hearing made up the AHG (AHG consists of five males and five females; age: 22.2 +- 7.2 years). The experimental approach and protocols were explained to AHG subjects using a sign language interpreter[10]. All of the volunteers gave their written consent before the tests started. They were all in good health and weren't taking any medications.

A simple hearing perception level methodology was created and proposed in this work to record the auditory evoked EEG signal from normal hearing participants. The experimental investigation applies a two-step methodology to collect AEP data from the subjects. The behavioural pure-tone audiometric test was used to determine the individuals' hearing threshold values after allowing them to participate in a hearing screening exam. A behavioural pure tone screening audiometry test was conducted using the SM960-D diagnostic memory audiometer. A pure tone stimulus was delivered via headphones. Behavioural pure tone stimulation at 1 kHz at various stimulus intensities ranges from 20 dB to 70 dB in the left and right ears[4]. Using a traditional pure-tone audiometric test, the ranges of frequency and sound intensity were selected.

The audiometric test outcomes for every subject were noted five times. Mean threshold values were calculated to make sure that the participants could hear and comprehend the specified sound stimuli. NHG subjects were those with a mean threshold hearing level of less than 20 dB. AHGs are those whose mean hearing threshold is higher than 20 dB. The EEG signals were recorded using the Mindset24 EEG amplifier portable bio signal acquisition system. Electrodes were inserted (frontal, occipital, parietal, temporal, central) over the areas FP1, FP2, F7, F3, FZ, F4, F8, T3, T5, C3, CZ, C4, T4, T6, P3, PZ, P4, O1 and O2 using the 10-20 electrode placement system (Standard Positioning Nomenclature, American Encephalographic Association).The left and right mastoids were used to create the reference electrodes[1].
The subjects were instructed to take off their eyeglasses, stop often nodding their heads, and refrain from moving their bodies in any way to diminish the effects of artefacts.An impulsive click sound with a 25 dBHL acoustic intensity and a frequency of 1000 Hz was played for the subjects to hear. For the subjects with normal hearing, synchronised stimuli and frequencies were delivered through headphones in the left and right ears with different sound intensities, and their related AEP signals were recorded. AEP signals were gathered for 10 seconds at a sample rate of 256 Hz.The same test was administered five times, each time with a one-minute inter-trial rest period. The procedure was then performed in the right ear at each frequency after recording AEP signals in the left ear. In order to increase the validity and reliability of the

data, two audiologists were asked to physically examine the collected AEP data from patients with normal and impaired hearing[7].

B. Pre-Processing using Chebyshev Filter:

Data preparation is the process of putting raw data into a format that is understandable. Given that we cannot work with raw data, it is also a crucial step in data mining. Before using machine learning or data mining methods, the data's quality should be examined. Data preprocessing is mostly used to assess the quality of the data. Here, data filtering is being employed as a preprocessing step**.** Data filtering is the process of choosing a smaller subset of your data set and using that subset for viewing or analysis.In order to determine the situations to include in the analysis through filtering, we must describe a rule or logic. [4]. Chebyshev filters are analog or digital filters that are classified into both type 1 and type 2 filters. Chebyshev fitters also have the ability to reduce error, and they are likewise regarded as a key stage in noise reduction because certain noises and artefacts can appear during EEG recordings of specific subjects. Chebyshev filtering is used as a pre-processing step. The Chebyshev second order filter provides a monotonic pass band and contains ripples only in stop band with steep roll off to the input AEP signals. The undesirable noises are eliminated in this step. The 19 electrode channels were recovered using a chebyshev filter following segmentation to 19 frames. Here, there is a separation of frequency bands. Frequency band ranges are Alpha(8-12Hz), Beta(13-30Hz), Gamma_1(31-45Hz), Gamma_2(46-99Hz)[7].

C. Feature Selection and Feature Extraction:

The best feature for the hearing threshold estimation is selected using the Genetic algorithm. Feature extraction is a dimensionality reduction technique divides a large amount of raw data into smaller, easier-to-process groups. Feature extraction refers to techniques for choosing and/or combining variables into features, which significantly reduces the amount of data that needs to be processed while accurately and fully describing the initial data set. When less resources are needed for processing without losing crucial or pertinent information, feature extraction might be helpful.Converting raw data into processable numerical features while keeping the original data set's content intact[10]. It yields superior results when compared to utilising machine learning on the raw data directly.Auditory Evoked Potential signals were then divided into frames, with 256 samples in each frame and a 50% overlap between them. After segmentation, the signals were filtered using the feature extraction technique. To extract the optimal feature for the dataset's study, the following features will be used: Spectral Entropy and Spectral Power.

D. Feature Classification using Neural Network:

The Elman network (ELN), a widely used architecture for feedback neural networks, connected the hidden layers to the input layers. To categorize the subjects with normal hearing and those with defective hearing, the feedback neural network models were set up using the input feature vector and two output neurons[4]. The feedback neural network models were set up with 19 input neurons representing the appropriate features for Power and Energy classification and two output neurons for normal hearing and defective hearing patients. The training samples were randomly chosen from all samples and trained to create a generalized feedback neural network model. A total of 200 samples make up the master data set. When the neural network had been trained with 140 samples of data (representing 70% of the master data set samples), the remaining 60 samples (30% of the master data samples) were used for testing. Tan sigmoid function was used to activate the 29 hidden neurons as well as output neurons. The data sample between the ranges of 0.1 and 0.9 was normalised using the binary normalisation procedure. The neural network model completed training with a 0.0001 tolerance and testing with a 0.1 tolerance. During the training sessions, the mean squared error (MSE) halting criterion was applied. The Elman network was trained using the gradient descent backpropagation with adaptive learning rate technique for each weighted sample.

IV. RESULTS AND DISCUSSION:

The impact of brain rhythm on hearing sounds at 1000 Hz and on auditory responses to the spectral power and entropy aspects have been studied using feedback neural networks. Table 1 displays the Elman Neural Network's Spectral power classification performance for the left and right ears at a hearing frequency of 1000 Hz whereas the Table 2 displays the Elman Neural Network's Spectral entropy classification performance for the left and right ears at a hearing frequency of 1000 Hz. In distinguishing people with normal hearing from those with defective hearing, Spectral Power had the highest classification accuracy, 90.32% and 92.45% for the left and right ears, respectively. Additionally, it was found that Spectral Entropy features had classification accuracy of 88.97% and 90.74% for the left and right ears, respectively, when distinguishing participants with normal hearing from those with defective hearing.

[1] SPECTRAL POWER		[2]	[3]
[4] EAR	[5] EPOCH	[6] MSE	[7] CLASSIFICATION ACCURACY
[8] L	[9] 6950	[10] 0.0048	[11] 91.52
[12] R	[13] 7630	[14] 0.0052	[15] 92.75

TABLE 1: Spectral Power results using Elman Neural network

SPECTRAL ENTROPY			
EAR	EPOCH	MSE	CLASSIFICATION ACCURACY
L	7640	0.0088	89.75
R	7980	0.0092	90.71

TABLE 2: Spectral Entropy results using Elman Neural network

V. CONCLUSION

In order to differentiate between patients with normal hearing and those who have defective hearing, spectral power and spectral entropy features were derived from the recorded AEP signals in this study. According to the study's findings, features may distinguish between people with normal and impaired hearing in terms of how the AEP signal changed in response to their hearing conditions. The Elman Neural Network feedback neural network model was used to categorise people with normal and impaired hearing. Furthermore, it appears that a stand-alone EEG-based hearing level system can be created and developed to identify hearing loss in all people, including newborns, infants, and people with multiple disabilities, helping to enhance their quality of life.

REFERENCES

[1] Paulraj M P, KamalrajSubramaniam, Sazali Bin Yaccob, Abdul Hamid Bin Adom, Hema C R, "EEG based hearing perception level classification using fractal features" , International Conference on Advanced Computing and Communication Systems (ICACCS -2013), Dec. 19 – 21, 2013.

[2] MdNahidul Islam, NorizamSulaiman, Mamunur Rashid, BiftaSama Bari, Mahfuzah Mustafa, "Hearing Disorder Detection using Auditory Evoked Potential (AEP) signals" , 2020 Emerging Technology in Computing, Communication and Electronics (ETCCE).

[3] KamalrajSubramaniamPaulraj M P Divya B S, "EEG based hearing states detection using AR modeling techniques." , 2016 IEEE EMBS Conference on Biomedical Engineering and Sciences (IECBES).

[4] Paulraj M P, Sazali Bin Yaccob, Abdul Hamid Bin Adom, KamalrajSubramaniam, Hema C R, "EEG based hearing threshold using fractal feature and neural network" , 2012 IEEE Student Conference on Research and Development.

[5] Emily Kubicek and Lorna C. Quandt , "Sensorimotor system engagement during ASL sign perception: An EEG study in deaf signers and hearing non-signers" , Volume 119, October 2019, Pages 457-469.

[6] SiqiCai ,Enze Su, LonghanXie , Haizhou Li., "A Spatiotemporal Attention Network for Decoding Auditory Spatial Attention From EEG", IEEE Transactions on Human-Machine Systems (Volume: 52, Issue: 2, April 2022).

[7] Paulraj M P, KamalrajSubramaniam, SazaliYaccob, Abdul Hamid Adom, Hema C R, " Auditory Evoked Potential Based Detection of Hearing loss: A Prototype System" , 2014 IEEE 5th Control and System Graduate Research Colloquium, Aug. 11 - 12, UiTM, Shah Alam, Malaysia.

[8] Neetha Das, Simon Van Eyndhoven, Tom Francart , and Alexander Bertrand, "Adaptive Attention- drive Speech Enhancement for EEG – informed hearing Protheses", 978-1-4577-0220- 4/16/2016 IEEE.

[9] MetinYarici, Mike Thornton, DaniloMandic, "Ear-EEG Sensitivity Modelling for Neural and Artifact Sources", arXiv:2207.08497; 18 Jul 2022.

[10] KamalrajSubramaniam, Sridhar K P, Paulraj M P, " Auditory evoked potentials based detection of hearing threshold using PSO neural network ",Pak. J. Biotechnol. Vol. 13 Pp. 357- 361 (2016).

[11] Dan Wu, "Hearing the Sound in the Brain: Influences of Different EEG Reference" , March 2018 | Volume 12 | Article 148.

[12] Elizabeth G. Blundon, Lawrence M. Ward, "Search asymmetry in a serial auditory task: Neural source analyses of EEG implicate attention strategies",DOI:10.1016/j.neuropsychologia.2019.107204 Corpus ID: 202794285.

[13] Álvaro GarcíaLópez ,Víctor Cerdán ,Tomás Ortiz ,José Manuel Sánchez Pena and Ricardo Vergaz, " Emotion Elicitation through Vibrotactile Stimulation as an Alternative for Deaf and Hard of Hearing People: An EEG Study" , *Electronics* 2022, *11*(14), 2196.

[14] Xiaoxuan Guo, Pradeep Dheerendra, Ester Benzaquén, W illiam Sedley, Timothy D Griffiths, "EEG Responses to auditory figure-ground perception" , Hearing Research 422 (2022) 108524.

[15] Yihan Wang, Zhixing Liu, Fei Chen, "An Eeg-Based Study of Auditory Sensitivity in Spatial Hearing", 2022 International Workshop on Acoustic Signal Enhancement (2022) 22189056.

[16] Karen A Gordon, Blake C Papsin, Sharon L Cushing, "EEG as a measure of neuroplasticity in children", Ent & Audiology news Volume 31 Issue 6 January/February 2023.

[17] Ghadah S. Aljarboa, Steve L. Bell, David M. Simpson , "Detecting cortical responses to continuous running speech using EEG data from only one channel" , International Journal of Audiology21 Mar 2022.

[18] Muncke, J.; Hoppe, U, "Prediction of the EEG for a speech in noise test using an auditory model", Journal of Hearing Science . 2022, Vol. 12 Issue 1, p139-139. 1p.

[19] SiyuanZang, Changle Zhou, Fei Chao, "Estimation of Event-Related Potentials from Single-Trial EEG", UKCI 2021: Advances in Computational Intelligence Systems pp 415–427.

[20] Lorna C. Quandta, Emily Kubicek , "Sensorimotor characteristics of sign translations modulate EEG when deaf signers read English" , Volume 187, December 2018, Pages 9-17.