A Deep Learning Based Approach In The Prediction Of Tinnitus Disease For Large Population Data

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***Abstract*— Tinnitus is a frequent sensory disorder that puts a lot of strain on the patient. Usually, tinnitus results from disturbances occurring to the sensory systems, such as the peripheral seldom central, the somatosensory system, the head and neck, or a mix of the two. This can be found in people with high stress, anxiety, depression, and hearing disorders. Although there is progress in the medical domain using artificial intelligence (AI), research related to tinnitus using AI is limited. This work aims to bridge the gap using deep-learning techniques for evaluating the patient record by examining various parameters. The proposed research also aims to target the same to understand the severity and possible recommendations for tinnitus disease. Our findings forecast how patients will react to tinnitus treatments. From the patients' electroencephalography (EEG) data, predictive EEG variables are extracted, and later feature selection approaches are used to determine the prominent features. The patient's EEG features are supplemented by AI algorithms for training and forecasting treatment outcomes. Higher accuracy levels of the proposed model using AI help the practitioners suggest the proper diagnosis for the patients and also check the patient's recovery over a period of time.**

Keywords*— *Tinnitus, Deep Learning, EEG, Feature Selection, Recommendations

I. Introduction

Tinnitus is a disturbing sound or noise in the head that has no external cause (pronounce it “TIN-NI-TUS”). While for some people it sounds like ringing, it can also sound like whistles, buzzes, chirps, hisses, humming, booming, or even screaming. The noise might seem to be coming from one or both ears, the back of one's head, or somewhere far away. It could be continuous or periodically occurring, stable or fluctuating. A condition known as pulsatile tinnitus causes some people to hear their heartbeat within their ears. One of the most common causes of tinnitus is damage that occurs to the hair follicles of the cochlea. The nerve impulses produced by sound waves are assisted by these cells. We generally don't notice the somatic sounds that our bodies naturally generate because we are listening to external sounds. Somatic sounds can be made audible to us by anything that interferes with regular hearing. For instance, if your outer ear is blocked by earwax, you might experience head sounds.

Managing tinnitus is notoriously challenging because it is often not a curable medical condition. The Food and Drug Administration (FDA) [2] controlled studies have not discovered a therapy for tinnitus that is an authorized medication. The use of artificial intelligence (AI) in the medical field has advanced. This would boost the effectiveness of therapy while minimizing patient stress and maximizing benefits. AI techniques like support vector machines (SVM) [3], multilayer perceptions (MLP) [5], logistic regression, naive Bayes learning, etc. have been used on neural data to categorize tinnitus. The disconnect between AI and hearing has deep roots. Cognitive behavioral therapy (CBT) and electroencephalography (EEG) are the most popular models applied to deal with neural data.

Internet-based cognitive behavioral treatment (ICBT) [4] is designed to treat tinnitus through the internet. The expenses of delivering an intervention using ICBT, which is often advertised as extensive and expensive, may be prohibitive. CBT therapies include a variety of elements. lifestyle suggestions, stress relief, musical enrichment, and therapeutic reflection. On visual comparable measures, daily reports of tinnitus discomfort and irritation as well as general well-being were gathered before, during, and after treatment. On these measurements, there were no noticeable effects, although loudness did exhibit a minor tendency to decline. Additionally, the patient completed a survey before and after the treatment, but no advantages were discovered.

The current research focuses on electroencephalography (EEG) [14], [15], [17], a relatively low-cost method that makes it possible to capture cortical electrical activity with high temporal resolution using electrodes placed over the scalp. A smaller amount of data features can simplify the model by removing irrelevant data using feature selection techniques. However, combining both temporal and spatial features is necessary to make the most of EEG data. An advanced analytical tool based on brain-inspired spiking neural networks (SNN) architecture, one of the most promising advances in artificial intelligence approaches, The brain-inspired SNN model can gradually pick up on brain dynamics that have been accumulated over time in a three-dimensional environment of artificial neurons and to identify significant trends in the collected data.

A popular technique for feature extraction from EEG data that is widely used in neurological diagnosis is subsampling

[11], [13], [14]. Using Fast Fourier Transform (FFT), EEG features were transformed and then visualized as a sequence of multispectral images of the topology of the brain. Deep neural networks are the foundation of one of the most widely used machine learning techniques. Different DNN architectures [15] [18], such as the convolutional neural network, have been suggested so far. Convolutional neural networks are more complex than other deep neural networks and are a desirable structure for deep learning since they require fewer factors to be considered. If the accuracy of the deep learning model is as high as expected, the practitioners will give treatment to patients and need to keep checking the status of the disease for a duration of time.

In this paper, we organized the data as, the information in the first section is a brief explanation of the cause of tinnitus, its effects, the prior models existing, and related works done previously. Then section 2 is about state-of-art methodologies, and section 3 describes the methodology proposed and is continued by results and discussion in section 4. The later part of the paper discusses the conclusion and prior suggestions.

II. Related Work

In this section, the work done by various people is related to tinnitus. Tinnitus does not have any complete, organized, and approved treatment. A lot of studies took place in various parts of the world, and a few useful treatment methods have been suggested to the patients.

In this part, we are going to discuss the methods used by various authors in their work related to tinnitus. The methods include the neuromodulation approach [1], [3], cognitive behavioral treatment (CBT) [2], [6], [7], tinnitus retraining treatment (TNT) [5], physiotherapy [8], pharmacologic treatment [8], [9], and auditory attention training. These are the models used to understand the level of impact of tinnitus and treat the disease.

The neuromodulation approach helps to understand the tinnitus impact and guides the practitioner to solve it. This neuromodulation is first done on animals and compares the results in them doing research and shows how the neuromodulation worked out in the case of animals but in some cases, this may not succeed in treating tinnitus in humans because it varies and can be harmful as well.

Cognitive behavioral therapy (CBT) [2], [6], [7] involves classifying people with the same level of symptoms into a category and monitoring their progress by giving the same medication and analyzing their sleep data, daily activity data, etc. This model gives better accuracy and is often used in society for studies and research work on various diseases [10]. This CBT is also used to treat insomnia and the irritating sound in the ear. This is a time-consuming process, and the result is not immediately shown; a period of time will pass before the treatment is performed.

Physiotherapy is performed on patients, which shows improvement in hearing, and it is performed under doctor guidelines. Auditory attention training is also used to treat hearing disorder and is an affordable way to treat patients. Pharmaceutical treatment has a probability of showing side effects even though it treats the disorder much more effectively. These methods must be performed under the doctor's guidelines and monitored by a professional [11].

Another important model is tinnitus retraining treatment (TNT) [5]. First, the patient's tinnitus level is observed, and hearing aids are suggested. The patient needs to use the aid, and the result immediately shows that it is an expensive method of treatment. The hearing aid needs to be brought back if it has issues and is not maintained carefully. This TNT does not show any side effects and is a very efficient method to treat tinnitus.

For the implementation of this project, the CBT [6], [7] (cognitive behavioral therapy) method was previously used. Although the efficiency of this method is very low, it is used because it gives a basic understanding of tinnitus. Currently, the upcoming model that is proposed is the EEG (electroencephalogram) [14], [19]. This EEG method offers high efficiency when compared to the previous model, and it offers unique information about the brain that is easy to study and whose response time is very short [17], [18]. So that it is very easy to find the tinnitus level of severity.

III. Methodology

In this section, we mainly focus on the tinnitus prediction and response to treatment. The study's objective is to create an artificial intelligence (AI)-based system that, utilizing computer models of brain data collected before and after tinnitus therapy, will detect and treat tinnitus. can predict how a patient's tinnitus severity will change over time. First, we must determine the Tinnitus Functional Index (TFI), a study created to assess how tinnitus affects many facets of life. The methods are demonstrated, and they include modeling EEG data in the frequency domain for pattern extraction, assessing the efficacy of the tinnitus therapy, and using functional connection networks as inputs to artificial intelligence algorithms. Using AI to make early predictions about tinnitus treatment outcomes with less data by estimating several parameters, our AI enables an optimized selection of therapy alternatives for patients. each treatment's reaction. EG sensors serve as informative elements in AI tools that advance the development of wearable diagnostics and prognosis and increase estimation accuracy. Tinnitus is a challenging sensory condition that has recently been treated with sensor technology, and the algorithm and its implementation offer new approaches. More people are now looking for long-term solutions in this area. By considering all these aspects, we are evaluating all of them by considering data sets.

Before the three months of treatment, data is collected from patients, and after the three months of treatment, the type of tinnitus is predicted. Later, the AI was trained by giving EEG features of frequency connectivity to predict outcomes. Calculate the TFI (tinnitus functional index) by using this formula. Add together all the valid responses for a specific subscale from that respondent. Divide by the number of valid responses that the respondent supplied for that subscale. multiplied by ten. Based on the value of TFI and some other condition on which AI trained, it will decide whether a patient is a responder or non-responder. The EEG features are transformed, and images are obtained; these images are mainly used for training. The patient wants to take different treatments, like the tinnitus severity numerical scale (TSNS) is used to measure the severity of tinnitus. Fig. 1 shows the prediction about the patient whether he/she is a responder or non-responder. A numeric rating scale is used to measure dimensions like strength (0–10 rating); the Depression Anxiety Scale (DASS) is used to measure some dimensions like depression, anxiety (self -reporting) and finally a schedule to note the affects of positives and negatives, a questionnaire containing 10 adjectives.

1.collection of data (before and after the treatment up to 3-months by using EEG)
2.Evaluate the type of Tinnitus.
3.Train the AI by giving EEG features of frequency connectivity and predict outcomes.
4.Calculate the TFI (Tinnitus functional index)
5.Based on TFI and some other activities AI will decide patient is responder or non-responder.
6.EEG features are converted from temporal domain to frequency domain by using fast Fourier transform (FFT) and get images, these images are used for training.
7.Tinnitus severity numerical scale (TSNS) is used to know the severity of tinnitus. Numeric rating scale is used to measure dimensions like strong etc. (0-10 rating).
8.DASS is used to measure some dimensions like depression, anxiety etc. (self-reporting).
9.PANAS (Positive and negative effect schedule) is self-reporting questionary contains positive and negative adjectives.
10.To identify the predictive pattern by using EEG data we have two approaches.
11.First approach is frequency domain images used to get the required output which is responder or non-responder.
12.Second approach is EEG functional connectivity used to get required output which is responder or non-responder.

Fig. 1. Prediction about the patient, whether a responder or non-responder

Later EEG data was used to get a predictive pattern in two different ways, which are:

A. Frequency domain images

It uses Delaunay triangulation with the help of the grid function to get the images, from which we are allowed to find the most efficient frequency bands. so that we can get three topographic maps for each frequency band. By using the frequency v-values, we can calculate the amplitude by averaging them and producing a single-frequency image. Finally, we use CNNs (conventional neural networks) for the frequency images to distinguish the responder from the non-responder.

B. EEG functional connectivity:

Basically, first we have to apply graph theory to the frequency domain so that we can get graph representation, which is the basic idea to implement. Next, we have to generate the EEG functional graph, which was used to input and train neural networks. Here, we are using the MLP classifier instead of CNN. Finally, if the change is present or not in the EFC, based on this EFC, we can decide whether the patient is a responder or non-responder. Fig. 2 is a diagrammatic representation of the methodology used in this paper, which depicts the flow of the method. When systematically following Fig. 2 we can derive to a conclusion whether the person's situation is responsive or not.

IV. RESULTS AND DISCUSSIONS

A. Datasets description

In this subsection, we are calculating the TFI, which plays a major role in predicting the severity. Here, we require two patient data sets, one of which is EEG and the other of which is behavioral and was collected both before and after the treatment. Behavioral data includes cognitive and psychological data, and TFI is calculated using behavioral data based on the results we used to classify responders and non-responders. TFL changes is computed as the difference between post-TFI and pre-TFI. If this difference is less than 4.8, these are considered responders; otherwise, they are considered non-responders. As fitted bio semi-headgear with electrodes was used by Parker. To guarantee uniform conductivity between the electrode and scalp, signa gel was applied to each electrode's positioning, and the processes were tracked on a PC. The down sampled 256-Hz EEG signals were used.

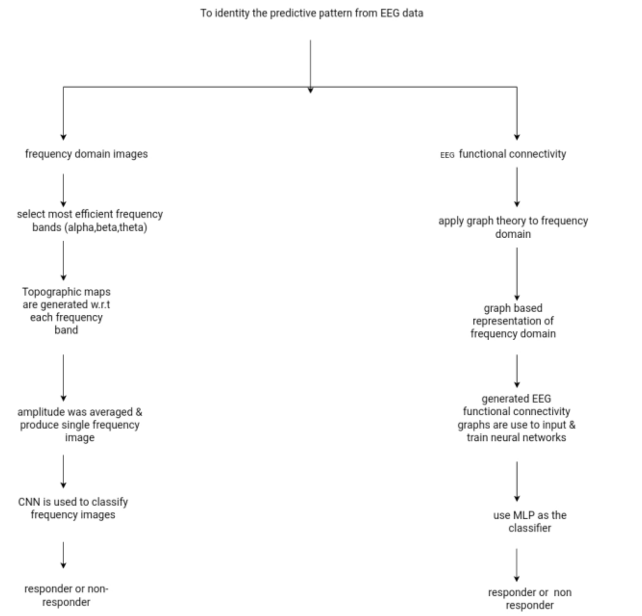

Fig. 2. Identify predictive pattern by using EEG data

EEG data is separated into 256 time point intervals. 6642 EEG recordings were obtained as a result, and deep neural networks were trained to predict whether or not the patient would benefit from tinnitus treatment.

Patients were utilized to determine the severity degree of the tinnitus (0, not an issue, to 5, very huge problems) using tinnitus severity numerical scales (TSNS). Five dimensions are perceived as being powerful, invasive, uncomfortable, how annoying the tinnitus was, and how simple it was to get rid of it. These parameters are measured on a numerical scale. (0–10 rating; 0—not a problem; 10—serious issue).Later, we also calculate some more activities that provide parallel information used for the treatment outcomes.

B. psychological functions:

The function we used here gives us the ability to analyze your own tinnitus severity. self-reporting techniques for both clinical and nonclinical populations to validate the elements of depression, anxiety, and stress. A questionnaire with ten components and each of which is scored on a scale of 1 to 5 (not very much) using neural networks and EEG to predict treatment outcomes: Currently, we are predicting treatment outcomes in this study using neural networks. In a similar vein, a computational AI model may be able to identify the baseline EEG patterns of individuals who may eventually react to tinnitus treatment. Two sorts of EEG-driven data were taken into consideration as neural network inputs in order to extract various kinds of prediction patterns from EEG data: EEG functional connectivity in the frequency domain. By using all of these, we can describe the EEG features and predict the outcomes.

C. Prediction of EEG Class in the Frequency Domain

This subsection deals with EEG and produces frequency images as outcomes. Within this article, we will describe the EEG and use deep neural networks to forecast the course of therapy. In order to use appropriate information, we chose to investigate properties in more frequently utilized frequency regions (beta is 14–30 hertz, alpha is 8–14 hertz, and theta is 4–8 hertz). At each electrode, for each frequency, we calculate the mean of the absolute values. Using the same methodology, we must determine the frequency for 64 electrodes based on the 10/20 system coordinates and 2D frequency images. Using Delaunay triangulation, data points were input and frequency domain pictures were created using a grid data tool; many points in the triangle region were then added in accordance with the triangle vertex values once this procedure was finished. Three topographic maps were created for each of the interest frequency bands after this procedure was repeated for all of them.

The temporal input to neural networks used for training is data from the 1st epoch. In this procedure, the EEG datasets were displayed as images, and a CNN, which is commonly used in image classification in deep learning, was deployed. CNNs are modeled after the visual cortex, where each sensory neuron's firing rate is influenced by a particular area of the retina known as the receptive field of a neuron. There are three primary layers of a CNN. All of these are separated into levels. Each area of neurons in layer i is linked by one neuron in layer i+1, Using a convolutional approach, which transfers the features from one layer to the following layers. CNNs employ activation mechanisms, They have therefore made improvements By resolving non-linear classification problems, computer vision systems can perform tasks like image classification, image segmentation, and object identification. CNNs were used in the current approach to divide responder and non-responder groups from EEG frequency pictures. EEG frequency inputs from 2D images that were 32 x 32 pixels in size were used to train the CNN model. In convolutional layers, we used ReLU, an activation function for deep learning models with nonlinearity. For final classification and prediction, the soft max (which transforms a vector of K real values into a K possible outcomes probability distribution) was used by using frequency images we can evaluate the functional connectivity.

D. EEG Class Prediction Based on Functional Connectivity:

From the above-mentioned frequency images, functional connectivity was created using EEG data and displayed the relationship over time between various brain regions. Each EEG frequency domain was converted into a frequency domain representation using graph theory. The frequency-domain correlation of each pair of EEG signals, p and q, is provided by the squared coherence. Here, three frequency bands are utilized. (Alpha, beta, theta).

$$\text{Cohxy}=|\text{Pxy(f)}|2\text{Pxx(f)}\cdot\text{Pyy(f)} \qquad (1)$$

where Pxy denotes the signal's x- and y-dimensional cross-spectral density. The power spectral density is shown by the parameters Pxx and Pyy. The created EEG functional connectivity graphs were fed into a deep neural network during training. However, we classify data using a multi-layer perceptron classifier (MLP). The responder group showed a greater increase in their edge functional connectivity (EFC). In the cortical areas, F1, Fz, FC1, FCz, FC2, C1, Cz, and C2 electrodes were employed. After therapy, functional connection spread across all electrodes and increased more noticeably in non-responder patients, here generated outcomes are used for the evaluation of results.

E. Results of outcome prediction by EEG data

a) EEG Frequency domain

As previously noted, we receive 6642 EEG samples, each of which has 256 data points and a record time of 1 s. These data are converted into frequency pictures before being sent into the CNN model as input. The CNN model was trained to predict the outcomes of tinnitus therapy using just the patients' baseline EEG data. The TFI scores of the patients following therapy were used to produce the class label information.

b) EEG Functional connectivity

In the subsection, the functional connectivity graphs were created from the raw EEG data after each pair of EEG channels' coherence was evaluated. The EEG channels serve as the nodes in the dynamic graph, the squared coherence between the channels is shown by the arcs. The time series data was created by updating the graph to show the evolution of the EEG signal over time. It can be used to train MLP-based deep learning neural networks.

For instance, after therapy, functional connectivity in additional brain regions containing Fpz, AFz, Fz, FCz, AF3, and AF4 was among those that responded. The non-responder group, on the other hand, did not see this increase. We employed MLP as a model to predict grade (treatment outcome) based on the 64*64 cell-sized EEG functional connectivity graphs. (Display of 64 EEG channel pairwise correlations)

c) Feature Selection for Tinnitus Predictive EEG Variable Identification

In this subsection, our main goal is to select an efficient feature. The tests used all 64 EEG channels to make treatment predictions for tinnitus. EEG channels unnecessary for tinnitus diagnosis were detected and removed to reduce data dimensionality and computational model complexity. To identify the key EEG features most significantly impacted by tinnitus therapy, we used different feature selection strategies. Evaluation of the contribution of EEG channels to the classification of EEG samples before and after treatment We developed a unique method termed "greatest change channel selection" (GCCS). Our feature selection method's primary objective was to identify the channels that had undergone the most treatment-related modifications.

To arrive at E ci, the average treatment impact on each EEG channel, Ci, is determined.

$$E(c_i) = \sum j_{(0\text{-}m)} \mid A\, C_{ij} - A'\, C_{ij} \mid / M \qquad (2)$$

where 'i' represent the i-th channel, j denotes the j-th patient, and M denotes the overall patient count. The patient's pre-treatment amplitude in EEG channel i is designated as Acij, A′Cij stands for patient j's post-treatment amplitude in channel I of the same EEG. Here, j's range is [1-8] while I's range is [1-64].

The GCCS feature selection technique was used to calculate amplitude changes in each EEG channel before and after therapy. We selected the top 30 EEG channels with the largest mean degree of treatment effect (Eci) in all patients. Model-based ranking is another title for the feature selection approach. First, we determined the average amplitude of each EEG channel (before and after therapy) for each patient. With 64 EEG channels and 8 patients, this resulted in two 64 8 matrices (one before and one after the treatment).

Then, an average of 8 additional patients were gathered for each channel, creating two 64-1 matrices. One reflects his EEG state before therapy. (Therefore, the before matrix) and the other the EEG state following therapy. (Called after-matrix). The feature-selection techniques mentioned in the section below used these two 64 x 1 matrices as input.The F-statistic and p-value were used as criteria in the model to rank the relevance of channels for the FR technique, and the higher the p-value, the more significant the associated channel. To determine this, the r-regression-based correlation between pre- and post-matrix data was calculated. Cross-correlations were then converted to F-scores to provide p-values. In the HF approach, we used the contamination calculated based on variance to rank the importance of channels in each tree.

The ET technique assigned a value to the impurity-based attributes in order to rank the channels' relevance. With rank, the channel's significance rises. The sum of the changes in a channel's values was used to assess its relevance. By using the feature significance attribute that the model returned, the RFE approach estimated the relevance of each channel. The present channel collection was then reduced in size by removing the least significant channels. This procedure was performed again with channels configured for the desired number of channels. Finally we get the outcomes based on this the efficiency is calculated.

E. Results:

In this subsection, we are discussing the performance of the different models with different accuracy levels. It was also able to predict whether patients would respond to treatment with up to 99% accuracy.

As we already know, the frequency-domain mode provides the most accuracy of our predictions, at 99.52%, while the functional connectivity-based model provides the maximum accuracy, at 99.41%. In training this model, 70% of the data is used for training and 30% for testing the performance of the network. The model also underwent 5-fold cross-validation, and the outcomes all scored above 90% accuracy. This indicates that our model is quite effective, and it is convincing proof that AI models may be able to forecast the results of tinnitus treatment based on electroencephalogram signal analysis. To further improve prediction accuracy, we applied five conventional techniques. To discover the best predictive EEG characteristics, feature selection approaches are used. Furthermore, we introduced GCCS, a new feature selection strategy that surpasses previous approaches in terms of prediction accuracy. The GCCS method identified the following EEG features as main predictors: FC3, P8, P4, T8, CP5.

TABLE I. RESULTS FOR THE TREATMENT OUTCOMES

MODEL	ACCURACY
TFI (Tinnitus functional index)	98%-100%
Frequency domain	98.54%
5-fold cross validation	99.37%
EEG functional connectivity	99.41%
GCCS	99.47%

TABLE II. ACCURACIES FOR FOLD CROSS-VALIDATION

Folds	Accuracy
5	99.42
6	99.52
7	97.13
8	98.57

TABLE III. RESULTS OF EEG DATA .

Prediction Label	Accuracy
Frequency domain mode	99.52
Functional connectivity based model	99.41
Training data	70
Testing data	30
Repsonder	99.2
Non-Responder	99.2

V. CONCLUSION

A very promising new topic in the treatment of tinnitus is AI diagnostic estimation. The application of AI diagnosis and prediction may result in more effective therapy goals. not only because of the wide and diverse range of available tinnitus treatment options but also because of the variability in individual tinnitus treatment outcomes. The treatment is completed quickly, allowing patients to receive more personalized and focused care. This study aimed to develop an artificial intelligence algorithm that could predict the outcome of tinnitus therapy. Different neural networks were utilized in this study to learn from the patient's EEG data and predict the result. Functional connection and EEG frequency characteristics were modeled using neural networks. To detect changes and trends in signals more reliably than by observing single time-domain data, use frequency-domain characteristics and function connectivity features. Because time domain parameters are impacted by signal structure, frequency domain and functional connectivity features provide effective categorization. We use three frequency bands to produce a low-dimensional representation in our work. In contrast, earlier research analyzed only frequency-domain data from a particular frequency band. Creating a low-dimensional representation using three frequency bands This improves the properties while reducing the computational load of the model. In the future, there are plans to develop real-time digital health systems based on several EEG parameters until the development of wearable devices that patients can use at home becomes possible. Finally, more tinnitus patients' EEG data should be used to build a more reliable AI model. As a result, we will be able to recognize a number of EEG channels linked to tinnitus and the effects of therapy.

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