Distinguish Hearing Impaired and Healthy Individuals based on EEG Topographic Map in Response to Tone Stimuli

- **Authors: Lead (main) author is first, often advisor's name is last (but varies)**
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- **Abstract: Paper overview – summary of importance, methods, results. Typically write this last (or at least rewrite it after you've completed the rest of the paper)**
  - The normal hearing threshold for healthy individuals is 0 to 20 dB. A person is said to be hearing impaired if their hearing threshold is greater than 35 decibels (dB) in the better hearing ear. This means it becomes challenging for the affected individual to communicate without the use of hearing aids or assistive devices.
  - There exists methods to diagnose hearing loss and differentiate healthy individuals from hearing impaired such as using hearing tests like otoacoustic emission testing, MRI scans and CT Scans. The goal of this study is to utilize scalp maps derived from spatial and temporal electroencephalography (EEG) data to distinguish between individuals with hearing impairment and healthy individuals. A deep learning approach based on convolutional neural networks (CNN) is designed to recognize patterns in the spatial and temporal EEG data that can accurately classify the two groups.
  - The EEG data of each individual consists of their electoral response to 1 kHz tones over many trials.
  - This raw EEG data is pre preprocessed to clean outside noise. Then, we extract the event related potential (ERP) features from the raw data and averaged them across all trials. ERP is a measurement of the brain's electrical response to a tone or stimuli. Then, we derived the scalp maps of each patient at every 10ms along their ERP waveform to enlarge the dataset of the CNN. We did this for 44 patients, half of which were healthy and half which were hearing impaired. These features are fed into a CNN to predict the class. The proposed approach is applied on the EEG dataset from the Selective auditory attention in normal-hearing and hearing-impaired listeners [Data set].
  - This approach achieves an accuracy of 84.37%
  - The use of advanced technology like CNNs can potentially lead to more efficient and accurate hearing impairment detection methods, benefiting individuals and healthcare professionals alike. More efficient and accurate hearing impairment detection methods are crucial for early intervention and appropriate treatment and can lead to cost savings in healthcare by reducing the need for more extensive treatments that could arise from untreated hearing loss.
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- **Introduction: Context, background, why should we care**
  - It is estimated that more than 50% of people over the age of 65 experience some form of hearing loss.
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    The goal of this project is to utilize scalp maps derived from spatial and temporal electroencephalography (EEG) data to distinguish between individuals with hearing impairment and healthy individuals. A CNN model will be trained to recognize patterns in the spatial and temporal EEG data that can accurately classify the two groups. The use of advanced technology like CNNs can potentially lead to more efficient and accurate hearing impairment detection methods, benefiting individuals and healthcare professionals alike.

- In this paper, we build upon a more elegant architecture, the so-called “fully conolutional network”. We modify and extend this architecture such that it works with very few training images and yields more precise classification

■ **Related research: Talk about nearest similar research**

Terminologies:

- EEG (Electroencephalography): EEG is a technique used to record the electrical activity of the brain. It measures the electrical potentials generated by the brain's neurons through electrodes placed on the scalp.
- ERPs (Event-Related Potentials): ERPs are specific components of the EEG signal that are time-locked to a particular event or stimulus, such as the presentation of a tone or visual stimulus. ERPs represent the brain's electrical response to these specific events and are characterized by distinct waveforms.
- Scalp Maps: Scalp maps, also known as topographical maps, are graphical representations of the spatial distribution of brain electrical activity recorded by EEG electrodes on the scalp. They provide a visual depiction of the magnitude and location of brain activity at specific time points or time intervals.
- Spatial EEG Data: Spatial EEG data refers to the patterns of electrical activity across different regions of the scalp. These patterns can be analyzed to identify brain regions involved in specific cognitive processes or responses to stimuli.
- Temporal EEG Data: Temporal EEG data refers to the patterns of electrical activity over time. It captures the dynamic changes in brain activity in response to events or stimuli.
- EEG Preprocessing: EEG preprocessing involves data cleaning and enhancement steps to remove noise, artifacts, and other sources of interference from the raw EEG signals. Common preprocessing steps include filtering, artifact removal, and baseline correction.
- Feature Extraction: Feature extraction is the process of identifying and extracting relevant features from the ERP waveforms. These features capture important characteristics of brain activity and are used as input to machine learning models for classification tasks.

Materials and Methods:

■ **Methods: Technical details of methods, algorithms, etc. including figures and Diagrams**

Database: In this study, we used a dataset containing EEG of 22 hearing impaired (HI) listeners with sensorineural hearing loss and 22 age matched normal hearing (NH) peers (between 51 - 76 years old). The data was collected from a previous study by Fuglsang et al. (2020). For this study, we are specifically looking at the tone stimuli experiment where during passive listening, event-related potentials (ERPs) were recorded while subjects were exposed to 1 kHz pure tones. These tones had a duration of 100 ms and were smoothly ramped using a 10 ms Hann window. The presentation rate of the tones was around 1 second on average, with random fluctuations of up to ±25 ms (jittered). Each subject underwent 180 repetitions of the tone stimuli. We used the same preprocessing techniques as they did.

The study consists of 4 main parts, including EEG signal processing, ERP extraction, extracting topographic brain maps and training, validating and testing the model. The first part includes EEG signal preprocessing and extraction of event related potential features. These features are used to draw the topographic brain map.

EEG preprocessing and most of the ERP extraction was already completed by the researchers of the dataset. The repository that contains code for analysis of auditory EEG data is located here: https://gitlab.com/sfugl/snhl

In the additional figures section of the repository at the bottom of 'project overview', Fig S2 contains a graph of the individual traces of ERP data averaged over the fronto-central electrode cluster, and the thin lines reflect the data from individual subjects. Thick lines show group mean averages. Within the repository there contains a script that calculates the mean average lines within the snhl/reports/paper/func/extract_erp.m file path.

ERPs are the features we are using to classify the two groups. Given each patient's ERP waveform which was up to 400 ms after the onset of tone stimuli, I created a script to loop through each patient's indiviudal ERP and extracted topographical scalp maps at every 10 ms intervals from 0 -400 ms, giving us 40 scalp maps per subject. 44 subjects x 40 images gives us a total of 1,760 images for our CNN model.

Convolutional Neural Network (CNN) Architecture:
We employed a CNN model to perform image classification on the dataset. The CNN model was implemented using the TensorFlow Keras library. The architecture consists of three convolutional layers, each followed by a max - pooling layer to extract relevant features from the input images. Specifically, the layers had filter sizes of 32, 64, 128, respectively with a ReLU activation function applied after each convolutional layer. Max-pooling layers with a 2x2 kernel were used to downsample the feature maps. The final layers included a flatten layer followed by a fully connected dense layer with 512 units and a ReLU activation function. A dropout layer with a dropout rate of 0.5 was applied to mitigate overfitting. The output layer consists of two units representing the two classes (Hearing Impaired and Healthy), with a softmax activation function to predict the probability distribution of each class.

Experiments:
Because the dataset is so small (1,760 images) I experimented with how I wanted to split my dataset. These are the results:

- **Results: Figures, graphs, and tables showing results – often comparing to state-**

of-the-art and with ablation studies. Clearly state/show what question(s) you answered: question and hypothesis, experiments to test hypotheses, what differentiates your methods/algorithms from others.

Experiment	Training Data	Validation Data	Testing Data	Test Loss	Test Accuracy
1	70%		30%	0.379341721534729	0.865234375
2	80%	10%	10%	0.22708694636821747	0.949999988079071
3	70%	15%	15%	0.4698977470397949	0.890625

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■ **Conclusions: Summarize findings (methods & results) and briefly describe future** Work

The CNN architecture employed in this study achieves a satisfactory performance of approximately 85%-95% accuracy in distinguishing between individuals with hearing impairment and healthy individuals based on scalp maps derived from spatial and temporal EEG data.

For future investigations, several potential avenues can be explored to further enhance the model's accuracy and generalization. Alternative machine learning methods beyond CNNs, such as support vector machines (SVM), random forests, or recurrent neural networks (RNNs), could provide valuable insights and potentially lead to higher accuracies. Additionally, conducting more fine-tuning of the model parameters and necessary optimizations can significantly improve its performance. Techniques like cross-validation, hyperparameter tuning, and regularization can be employed to fine-tune the model.

The CNN architecture achieves good performance of around 85%. For future steps, we can look into different machine learning methods to achieve higher accuracy. We should also create different models that alter Model Optimization and Tuning: Fine-tune the model parameters and perform any necessary optimizations to improve its performance. This may involve techniques such as cross-validation, hyperparameter tuning, and regularization.

■ **Acknowledgments: Funding sources, collaborators (especially funding – collaborators are usually already in the authors list)**

■ **References: Citations (only ones actually used in the paper), follow norms in publication venue on the appropriate number**