EXPLAINABLE DIAGNOSIS OF MIGRAINE VIA DEEP LEARNING THROUGH THE USE OF EEG DATA

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ABSTRACT

Migraines are a highly prevalent and costly disorder which is hard to diagnose and typically requires a specialist reviewing a patient's history. As a result, migraines remain underdiagnosed and hence undertreated. Electroencephalography (EEG) data has previously been used to diagnose various neurological disorders such as epilepsy, motivating the use of this data to develop a model for the automated diagnosis of migraines. In this paper, we propose a straightforward approach to automated migraine diagnosis via the fine-tuning of the ResNet-50 architecture on spectrograms of EEG data. We demonstrate that our proposed model has comparable performance to recent methods of automated migraine diagnosis at 96.3% accuracy. Furthermore, we show that we can apply methods in model explainability to highlight aspects of EEG data which our model places more importance on, making it more suitable for clinical use where the explainability of model predictions play an important factor in clinical adoption.

INTRODUCTION

Migraine is a complex neurological disorder that affects more than a billion individuals every year. Globally, migraine ranked as the second leading cause of disability-adjusted life-years (DALYs) lost to neurological disorders in 2016, contributing 16.3% [95% uncertainty interval (UI): 11.7–20.8] of the total attributable DALYs[1]. The International Classification of Headache Disorders (ICHD-3) defines migraine as a recurrent primary headache disorder that lasts for 4–72 h. The headache is usually single, pulsatile, moderate or severe, aggravated by physical activity and accompanied by nausea, photophobia and phonophobia[2].

The diagnosis of migraine is usually carried out by a specialist through analysing the patient's history, physical examination and fulfilment of the criteria given by the ICHD-3[2] [3]. However, migraine remains underdiagnosed and undertreated [4], and may sometimes be misdiagnosed, even by healthcare professionals [5]. As such, methods for more accurate diagnosis of migraine are necessary.

Electroencephalography (EEG) is a non-invasive method for recording the brain's spontaneous and rhythmic electrical activity, from the placement of electrodes on the scalp. EEG has been used to diagnose various neurological disorders such as epilepsy[6] and sleep disorders[7]. Several studies have reported frequency-specific differences in power spectra between interictal migraine sufferers and healthy patients. O'Hare et al.[8] analysed resting-state alpha band oscillations in the visual areas of the brain. They found an increase in lower alpha band (8 – 10 Hz) power in migraineurs compared to control. Bjørk et al.[9] reported that migraineurs had globally increased theta activity during rest.

Cao et al.[10] found that in interictal migraineurs, EEG power was lower in fronto-central and parietal regions in all frequency bands excluding gamma. Chamanzar et al.[11] analysed EEG signals of interictal migraine sufferers and healthy controls exposed to visual and auditory stimuli and at rest. They found abnormal brain connectivity in migraineurs with or without stimulus. Many more reported correlates, sometimes contradictory, exist.

Because these feature-based correlates are contradictory and disputible in the literature, some researchers have turned to machine and deep learning diagnosis methods which can also reveal EEG correlates that are indicative of migraines. Aslan et al.[12] used Tunable Q-Factor wavelet transform and ensemble learning techniques to distinguish between the EEG signals of migraine patients in interictal state and healthy controls, achieving a 89.6% accuracy. Subasi et al.[13] used random forest and discrete wavelet transform, alongside photic stimulation of migraineurs during the experiment, achieving an accuracy of 85.95%. They also found that EEG signals acquired during photic stimulation increased classification accuracy. Lastly, Göker used a bidirectional long-short term memory deep learning model, achieving a performance of 95.99%.[14]

In this paper, we introduce a deep learning approach to diagnosing migraines. Our proposed model applies a short-time Fourier transform on EEG data, before passing the data into a fine-tuned version of ResNet-50. Our model performs on par, if not better than existing models, while requiring fewer channels than most models. In addition, our model provides visual explainability with HiResCAM, which not only provides quantifiable insights into the outputs of the deep learning model but also allows for medical professionals and researchers to verify the conclusions of the model.

METHODOLOGY

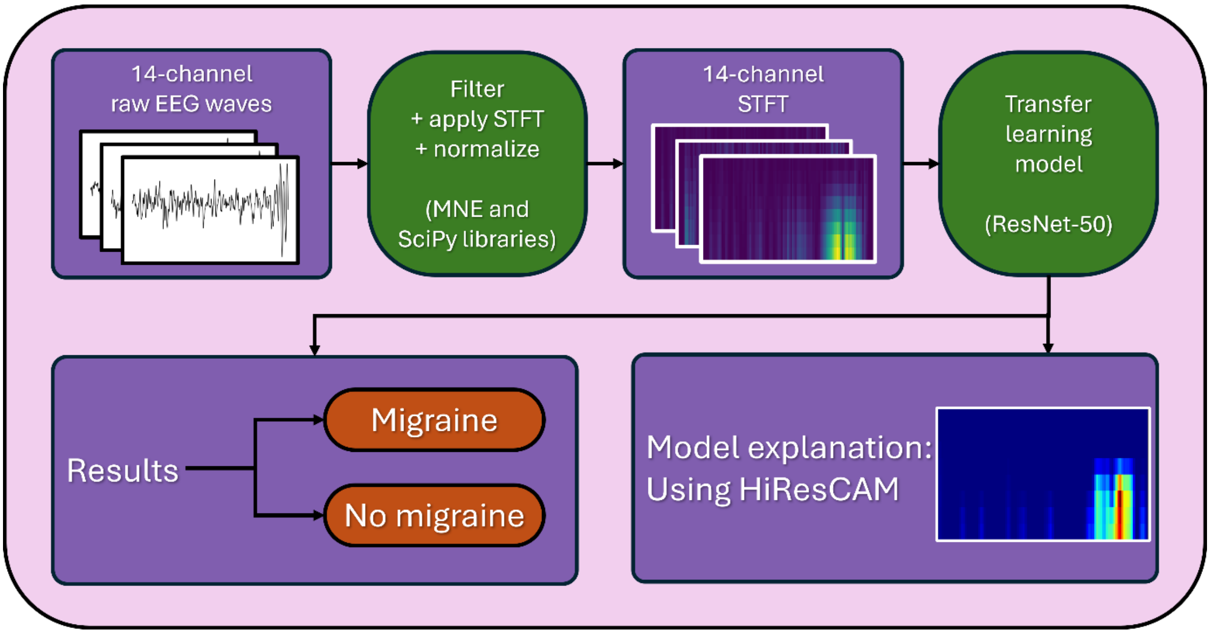

Figure 1: Overview of our approach to model development and explainability. Given 14 channel raw EEG waves segmented into 4 second intervals, we apply a short-time Fourier transform (STFT) and normalize afterwards to the interval of [0,1] for better model performance. We then train ResNet-50 on this data to produce our final model with the capability to diagnose, based on given 14-channel EEG waves, whether the source of the EEG waves was a migraineur or non-migraineur. Furthermore, we apply HiResCAM, a class activation mapping method, to determine which parts of the EEG the model places more importance on.

Task definition: We structure our task as a binary classification problem, where the aim of our model is to correctly classify given multi-channel EEG samples of duration L as either from migraineurs or healthy control samples. In this paper, L is of duration 4s.

Dataset: For our dataset, we used a publicly available dataset of high-density (128 electrodes) EEG recordings, of 17 individuals with migraine in interictal periods, and 18 control subjects[15]. These recordings were acquired during resting state along with auditory tones and visual checkboard stimuli. All recordings were used for training, evaluation, and testing, with a traineval-test split of 64:16:20. Out of all 128 channels available in the dataset, we selected channels Fpz, Oz, F7, F8, C3, C4, P3, P4, O1, O2, C5, C6, T7, and T8 channels, based on Ullah et al., 2024[16].

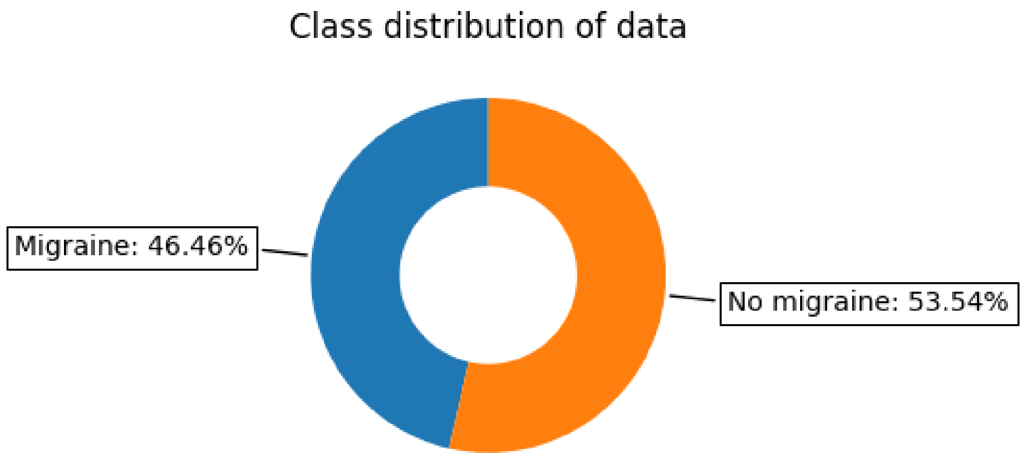

Figure 2: Donut chart showing the class distribution of migraine/no migraine episodes in our data. The episodes are of roughly even distribution.

Data preprocessing: We filtered these signals using a Butterworth filter to remove frequencies below 0.5 Hz and above 32 Hz to isolate beta, alpha, theta and delta frequency bands, and a notch filter at 60 Hz to remove oscillations from mains electricity.

After segmenting EEG recordings into 4-second episodes, we applied the short-time Fourier transform (STFT) onto each episode with a sampling frequency of 512 Hz to match the sampling frequency of the dataset, with the window being shifted by 20 samples in each step. For the STFT windowing function, we utilised a symmetrical Gaussian window with a size of 128 samples, and a standard deviation of 8. The magnitude from the STFT was normalised by dividing every value by the largest magnitude in the STFT for each episode. The result of our data preprocessing is 14 normalised spectrograms of the EEG data, 1 for each channel.

Model description: After preprocessing of our data, we fine-tuned the whole of ResNet-50 to obtain our model. To obtain model predictions, the required input is 14 normalised spectrograms of filtered EEG data, and the output is a singular probability of whether the source of the EEG data is a migraineur or non-migraineur.

Model explanation: To obtain our model explanation, we applied HiResCAM onto our fine-tuned ResNet-50, to explain the importances the model places upon specific frequencies. HiResCAM element-wise multiplies a feature map with the gradients in a selected layer of a convolutional neural network (CNN). Higher values in the output indicate higher model importance for a particular area of the feature map. Our use of HiResCAM expands upon the approach taken upon in Aslan, 2023[18], where Grad-CAM, a similar model explanation technique, was also used for explainability, but provides less faithful visual explanations than HiResCAM[17]. Grad-CAM visualisations of our model are included in Appendix B. HiResCAM was applied onto the first CNN layer of the fine-tuned ResNet-50 model. An explanation for why HiResCAM was applied to this layer, and not any of the ResNet-50 blocks, is include in Appendix C. We then proceed to average the HiResCAM values for each channel over all 4-s episodes.

Statistical analysis: We then perform a statistical analysis for frequency bands with the highest average HiResCAM values. After squaring the magnitude of the STFT to obtain the power spectral density, we perform Welch's t-test to see whether the difference in band power between migraineurs and non-migraineurs is statistically significant.

RESULTS

	Classification method	Number of channels used	Accuracy (%)
Aslan, 2021[12]	Tunable Q-Factor wavelet transform, ensemble learning	128	89.6%
Subasi et al., 2019[13]	Discrete wavelet transform, random forest	18	86.0%
Göker, 2023[14]	Welch's method, Bidirectional long-short term memory	128	96.0%
Ullah et al., 2024[16]	Logistic regression	14	99.7%
Aslan, 2023[18]	Continuous wavelet transform, CNN	128	100%
Orhanbulucu et al., 2023[19]	Continuous wavelet transform, transfer learning via AlexNet	64	99.7%
Proposed method	Short-time Fourier transform, fine-tuning via Resnet-50	14	96.3%

Table 2: Comparison of our method to previously reported methods for migraine diagnosis. Our method is comparable to current methods while also having the crucial benefit of explainability for practical usage. All methods use the same dataset by fijdpsoaj 2021, except for Subasi et al., 2019.

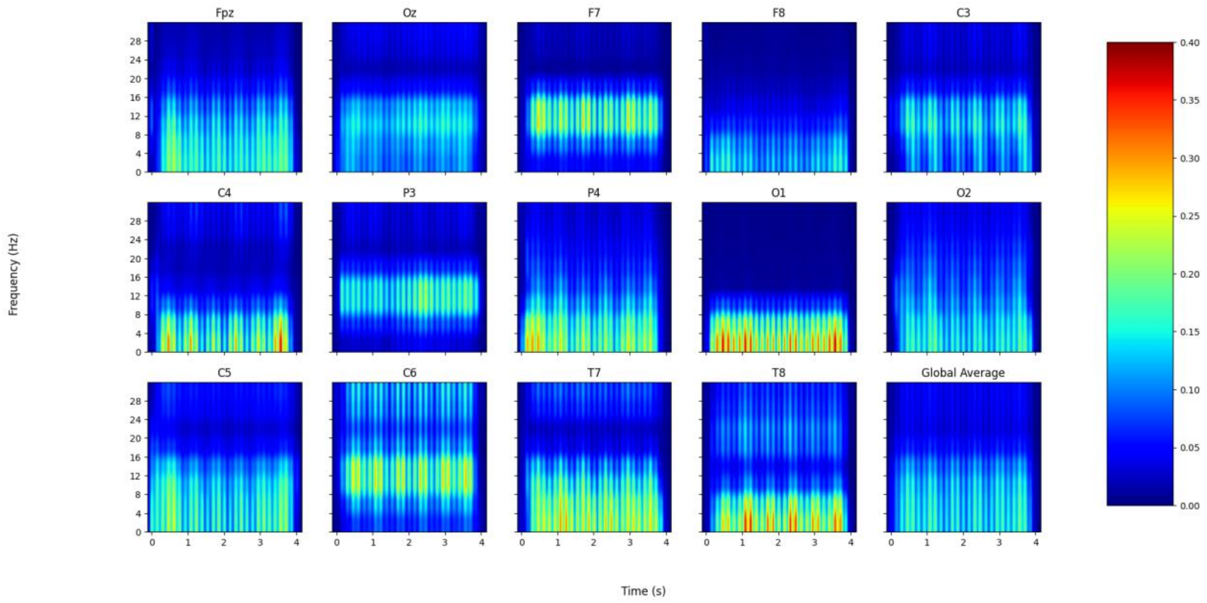

Figure 3a: HiResCAM values for each channel, averaged over all 4-s episodes. Bands with higher values from HiResCAM in the heatmap represent regions (corresponding to frequency bands in time) of higher saliency used in model predictions. In Appendix A, we show that such visualisations are accurate in place of visualisations for only migraines or only non-migraines, as model importances align for both migraines and non-migraines. The bottom right box refers to the average HiResCAM values of all channels, across all episodes. Grad-CAM visualisations of our model are included in Appendix B.

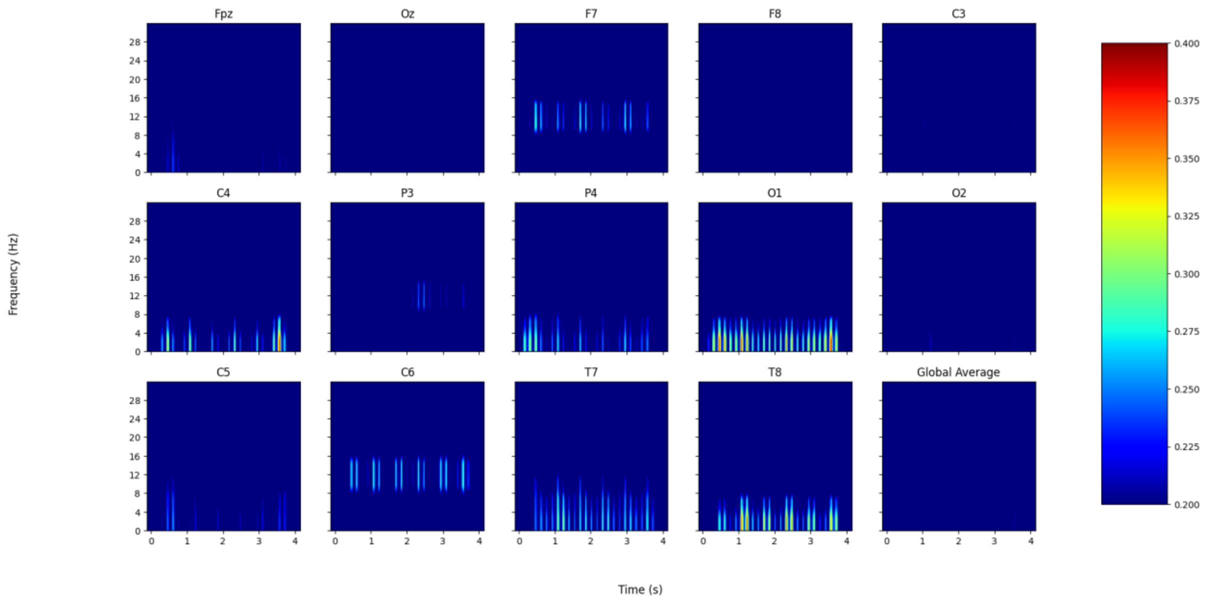

Figure 3b: produced with the same procedure as Figure 3a, but with the lower cutoff of the heatmap at 0.2 instead of 0, for better visibility of more significant model importances.

DISCUSSION

From the results, we conclude that our fine-tuning approach performs comparably with previous research, while outperforming approaches proposed in Aslan, 2021[12], Subasi et al., 2019[13], and Göker, 2023[14]. We also show that we are able to achieve model performance comparable to previously reported deep learning methods, using data from just a subset of electrodes identified in Ullah et al., 2024.

Importantly, our analyses of features learnt by the model reveal EEG correlates of migraine activity. Based on the HiResCAM values, our model places emphasis on the electrode-frequency combinations (in order of their appearance in Figure 3b), C4: 0-8, O1: 0-8, T8: 0-8. Further statistical analysis was carried out on these electrode-frequency combinations, to confirm that significant differences exist between migraineurs and control.

For C4, band power from 4-8 Hz and 0-4 Hz were significantly less for migraineurs compared to control ($p < 0.01$ and $p < 0.05$ respectively). For O1, band power from 0-8 Hz was significantly less for migraineurs compared to control ($p < 0.01$). For T8, band power from 0-8 Hz was significantly less for migraineurs compared to control ($p < 0.01$).

The correlates found from C4 have some consistency with prior research by Cao et al., 2016, which found that in interictal migraineurs, power was lower in fronto-central and parietal regions in all frequency bands except gamma[10].

Other electrode-frequency combinations that the model placed emphasis on were, F7: 8-16, P4: 0-8, C6: 8-16, T7: 0-8.

We believe that with high accuracy and low electrode use count, our model can provide a cheaper and less time-consuming method of migraine diagnoses, with only slight decreases to accuracy. Moreover, the explainability of our model allows for clinicians to view our model with a higher level of trust, as they are able to understand the reasoning behind the outputs of our model. Possible future work could include investigating whether further removing certain electrodes without compromising on accuracy is possible, because certain electrodes like F8, P3, P4 and O1 are not of particular importance to the model according to Figure 3a.

CONCLUSION

In this paper, we have shown a 14-channel explainable fine-tuning approach to migraine diagnosis, with comparable if not better accuracy than other models. Using HiResCAM for explainability, we have shown how our model corroborates with some pre-existing neural correlates, while finding new ones in the process.

ACKNOWLEDGMENT

We would like to acknowledge the following GitHub repo for some of our code: https://github.com/SSaeedinia/EEG-Classification-_Epilepsy-vs-Migraine

We also like to acknowledge our mentors, Dr Chieu Hai Leong and Dr Ang Wan Yu Grace, for their technical support and advice throughout our project.

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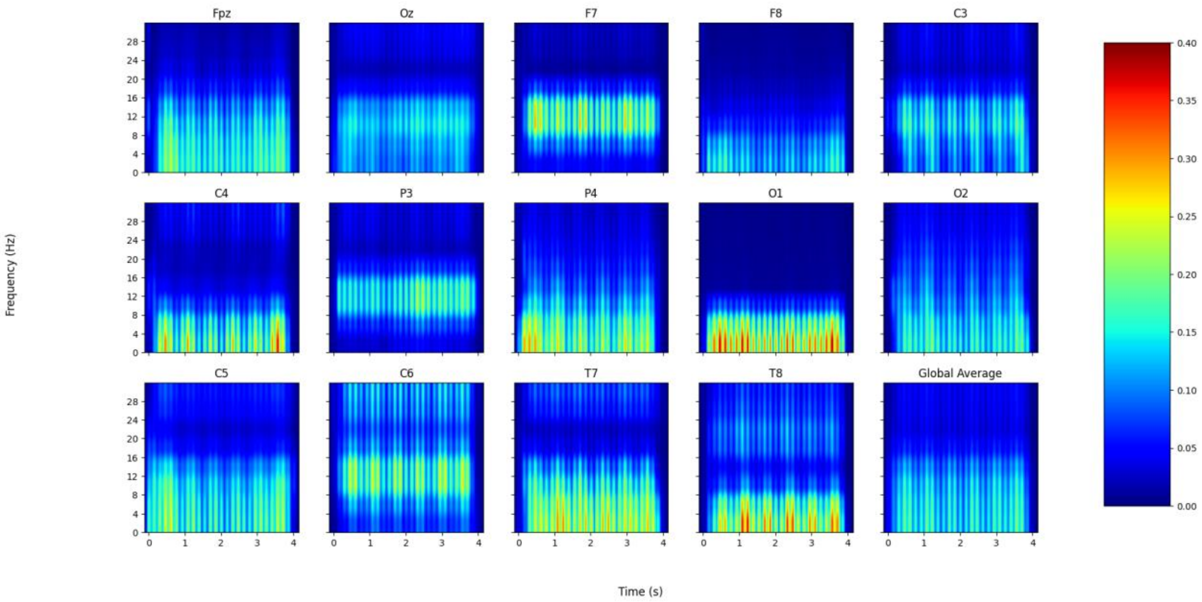
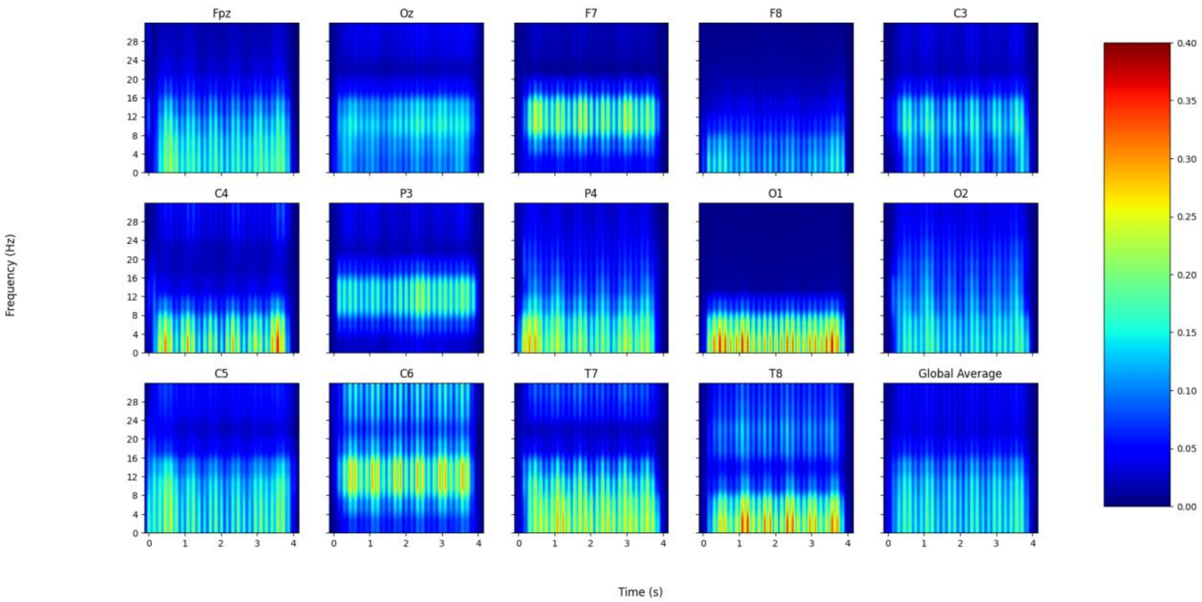
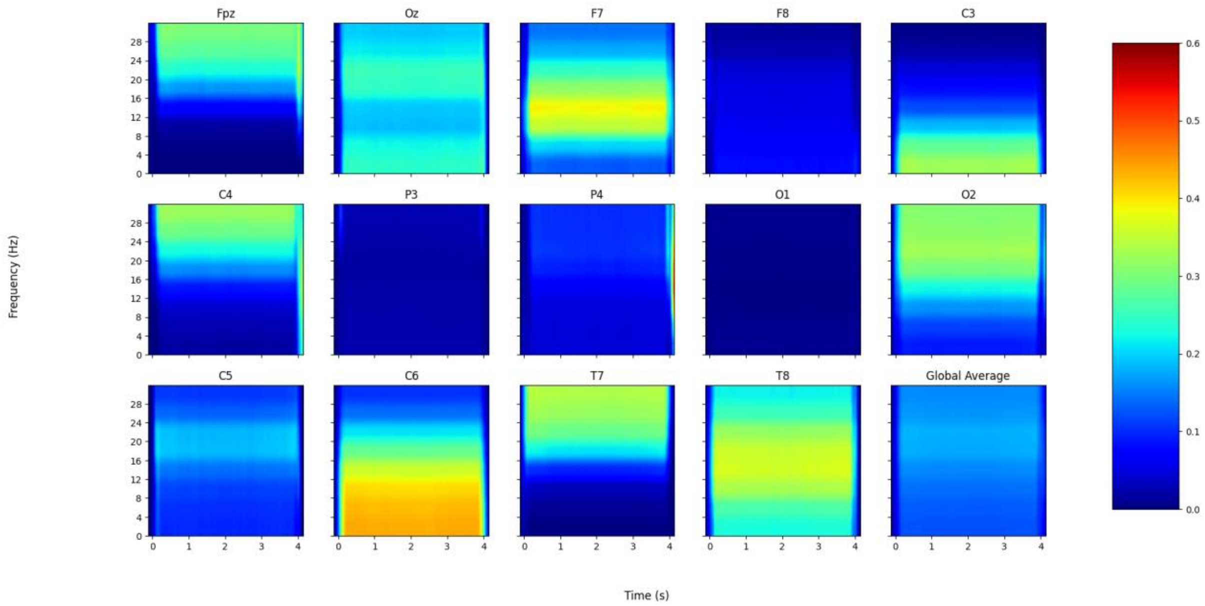
APPENDIX A: HIRESCAM MIGRAINE AND NON-MIGRAINE VISUALISATIONS

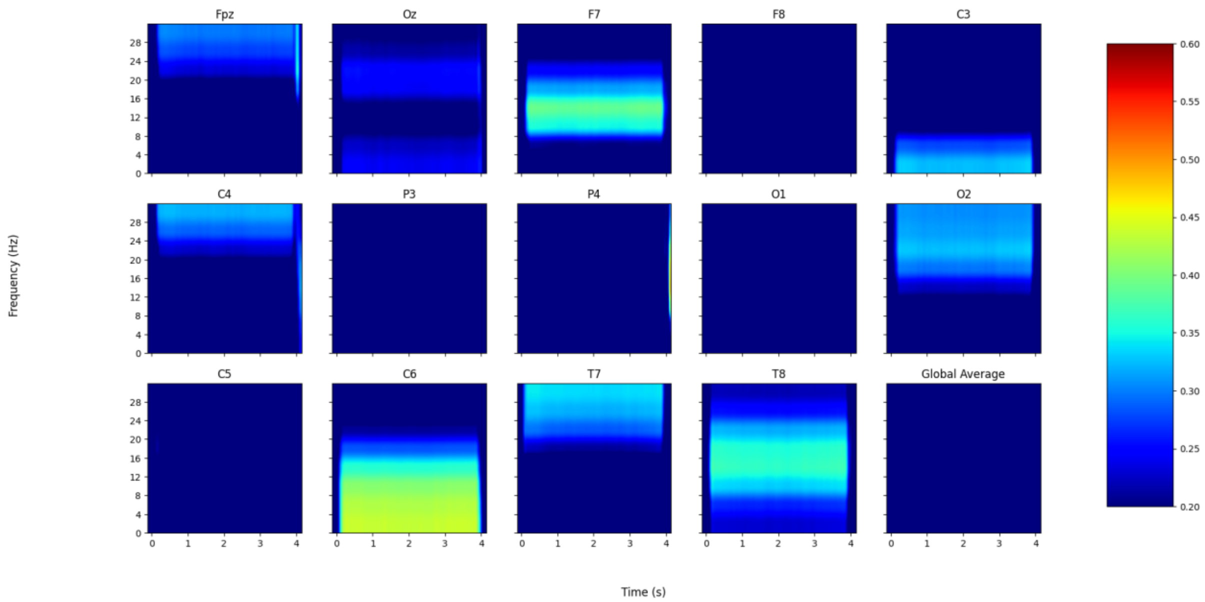


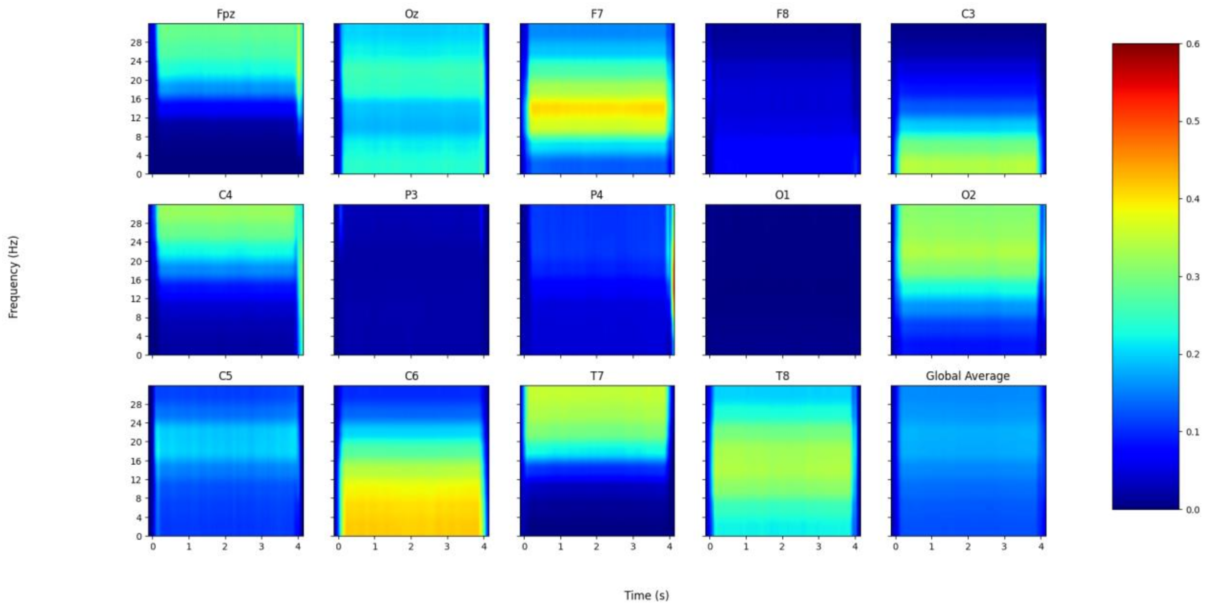


Figures 4a, 4b:The top figure shows the average HiResCAM values for migraines, while the bottom figure shows that of non-migraines; based on these HiResCAM heatmaps we can see that the frequency bands which are of more importance to the model line up with both migraines and control, with the only difference being the degree of importance placed on particular frequency bands differing slightly. As such, a visualisation of the average of all HiResCAM values for each channel is a valid representation of model importances placed on particular frequency bands.

APPENDIX B: GRAD-CAM VISUALISATIONS







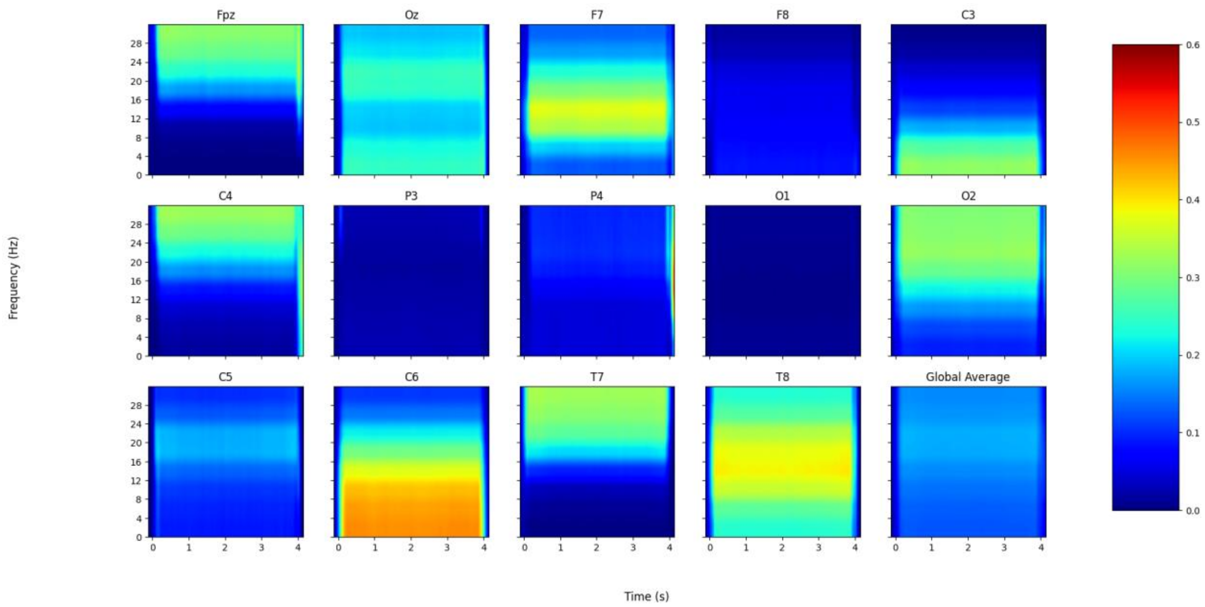


Figure 5a, 5b, 5c, 5d: In order, these figures refer to the average Grad-CAM values for both migraines and no migraines with no heatmap lower cutoff; both migraines and no migraines with a heatmap lower cutoff of 0.2; migraines only with no heatmap lower cutoff, no migraines only with no heatmap lower cutoff.

APPENDIX C: HIRESCAM LAYER SELECTION

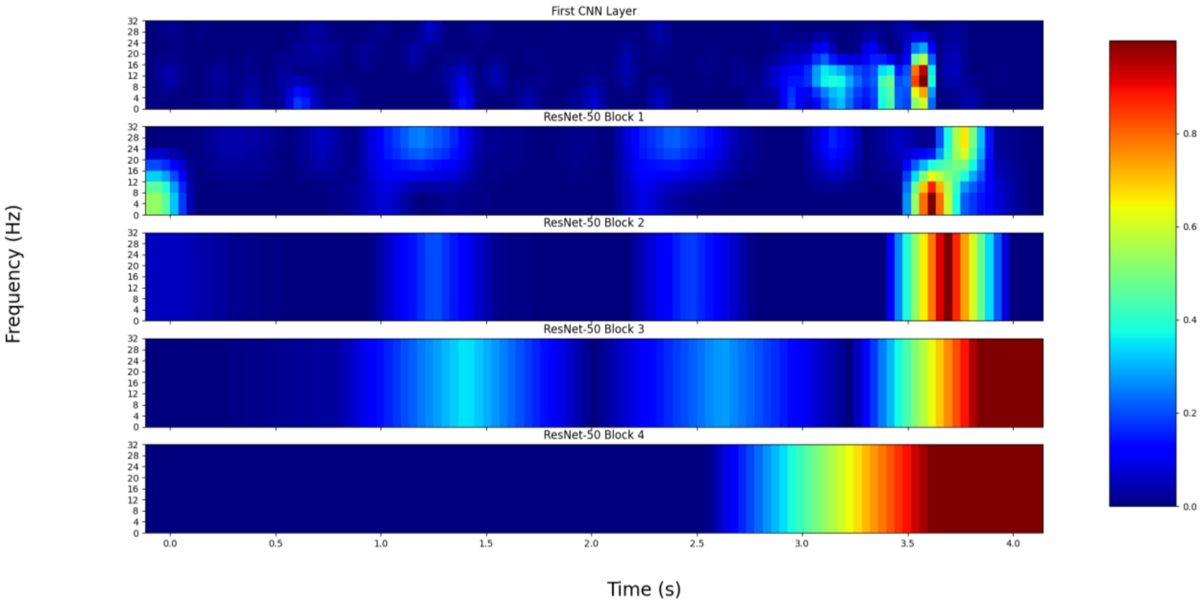


Figure 6: HiResCAM visualisation of the first CNN layer, and each of the four blocks in the ResNet-50 model. While the first CNN layer exhibits areas of importance in a localised area in the 4-s episode, starting from ResNet-50 block 1, the HiResCAM output shows that all frequency bands in a period of time are important to the block, instead of specific frequency bands at specific periods of time. As such, it is more useful to apply HiResCAM on the first CNN layer, in order to find specific frequency bands of importance.