YDSP Young Defence Scientists Programme
DSTA Defence Science & Technology Agency
DSO National Laboratories

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 ResNet50 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

Problem

Migraines affect more than a billion individuals every year

Undertreatment, underdiagnosis and misdiagnosis

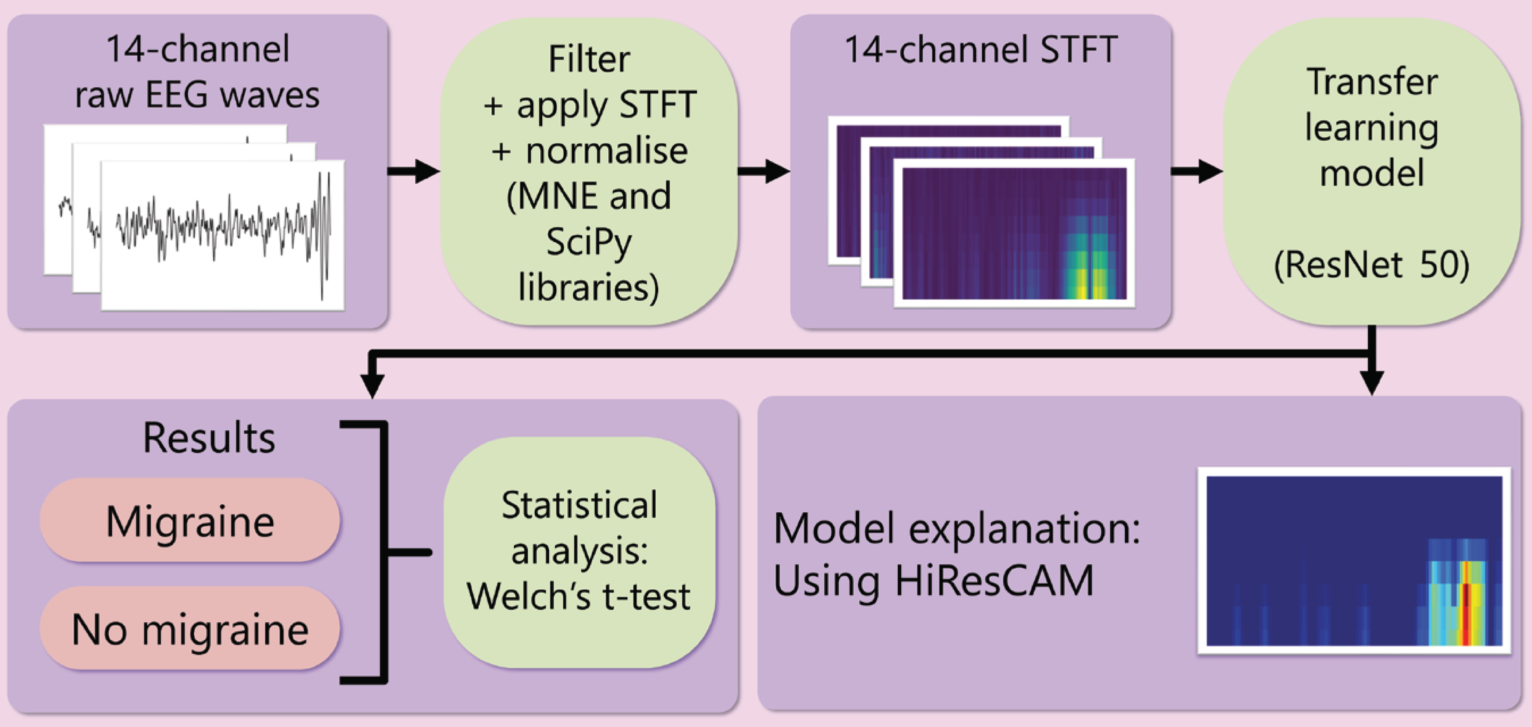
Inconsistent EEG correlates

Solution

Explainable and **high performance** deep learning model

METHODOLOGY

Dataset: Publicly available 128-channel EEG (17 migraineur, 18 control), train-eval-test split 64:16:20, using 14 channels.[1]



RESULTS

Table 1: 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 Chamanzar et al., 2020[1], except for Subasi et al., 2019[2].

	Classification method	Number of channels used	Accuracy (%)
Aslan, 2021[3]	Tunable Q-Factor wavelet transform, ensemble learning	128	89.6%
Subasi et al., 2019[2]	Discrete wavelet transform, random forest	18	86.0%
Göker, 2023[4]	Welch's method, Bidirectional long-short term memory	128	96.0%
Ullah et al., 2024[5]	Logistic regression	14	99.7%
Aslan, 2023[6]	Continuous wavelet transform, CNN	128	100%
Orhanbulucu et al., 2023[7]	Continuous wavelet transform, transfer learning via AlexNet	64	99.7%
Proposed method	Short-time Fourier transform, fine-tuning via ResNet 50	14	96.3%

RESULTS (CON'T)

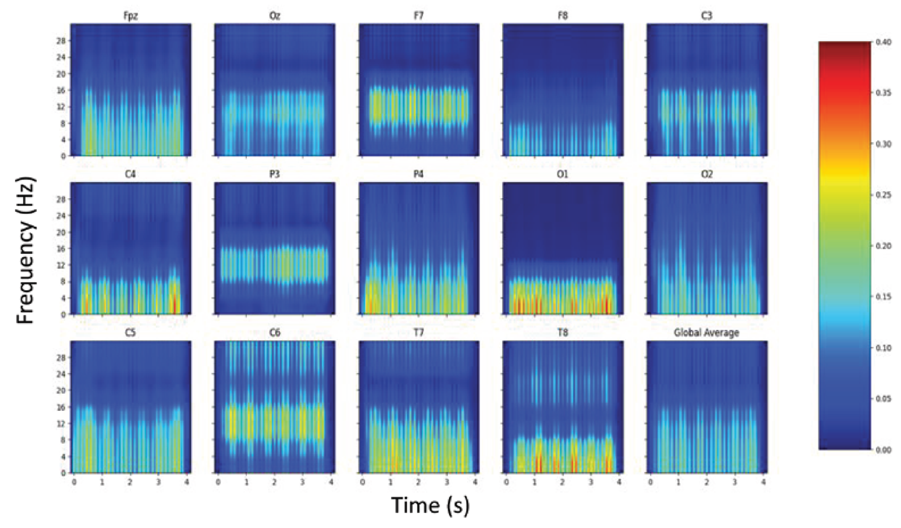


Figure 2a: HiResCAM values for each channel, averaged over all 4-s episodes. Bands with higher values from HiResCAM in the heatmap represent regions (corresponding to frequency bands in time) of higher saliency used in model predictions. Such visualisations are accurate in place of visualisations for 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.

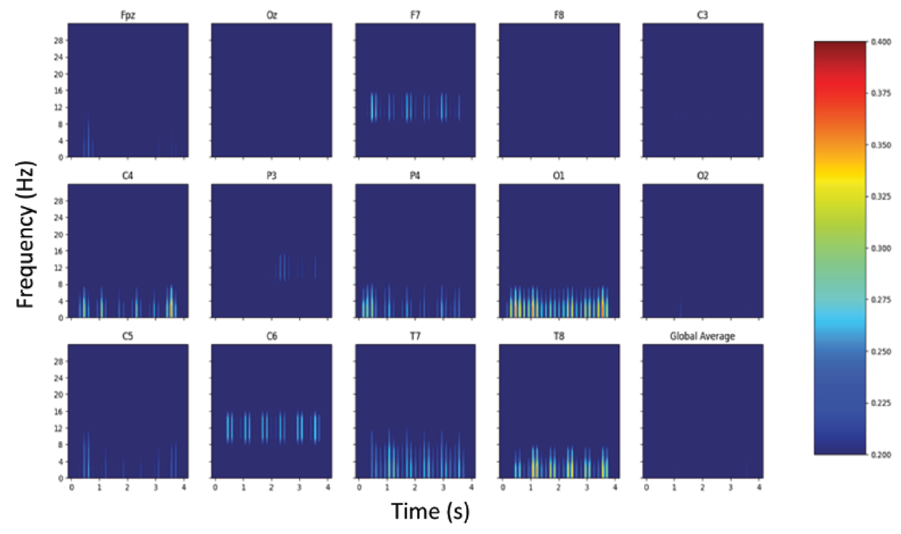


Figure 2b: produced with the same procedure as Figure 2a, but with the lower cutoff of the heatmap at 0.2 instead of 0, for better visibility of more significant model importances.

- We conclude that our fine-tuning approach performs comparably with previous research, while outperforming approaches proposed in Aslan, 2021[3], Subasi et al., 2019[2], and Göker, 2023[4]. 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[5].
- Based on our HiResCAM values, our model places emphasis on the electrode-frequency combinations (in order of their appearance in Figure 3b), F7 (8-16 Hz), C4 (0-8 Hz), O1 (0-8 Hz), P4 (0-8 Hz), O1 (0-8 Hz), C6 (8-16 Hz), T7 (0-8 Hz). T8 (0-8 Hz). Further statistical analysis showed that the power in these highlighted frequency bands were significantly lower ($p < 0.05$) in migraineurs compared to controls.
- The correlates found from C4 have some consistency with prior research, which found that in interictal migraineurs, power was lower in fronto-central and parietal regions in all frequency bands except gamma[8].

CONCLUSION

End product

Created an **explainable** and **high performance** deep learning model with **low electrode use count**

Model explanation **corroborates with pre-existing neural correlates, increasing trustworthiness** amongst clinicians

Future work

Investigate **removing certain low-importance electrodes** without compromising on quality

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