1.1 Pain Detection

The objective of pain detection is to objectively assess pain from EEG signals. This is implemented through AI, specifically a Deep Learning (DL) algorithm. DL algorithms can make predictions and classifications by identifying patterns in data. Typically, DL algorithms require large datasets for effective training and classification. However, for this article, access to substantial data containing scalp EEG recordings during acute pain sensation was unavailable. To address this limitation, a novel dataset was created by introducing pain-correlated signal artifacts into EEG recordings where no actual pain was experienced. Pain artifacts were defined from studying articles: [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26] and [27]. A pain artifact is defined as:

$$A = \{b, c, e, d, t\}(1)$$

where (b) represents the affected band ranges. (c) represents the channels affected. (e) signifies the effect. (d) represents the delay. (t) represents the duration. The EEG recordings were obtained from one of the authors during daily activity. The EEG data was sampled into smaller sections. For half of the samples, a pain artifact, timing, and intensity level ranging from 1 to 10 were randomly selected. The remaining samples are not imposed with pain. The chosen artifact, timing and intensity are saved as labels for the AI algorithm.

The set of all the samples are defined as:

$$S_n = \{S_1, S_2, \dots, S_N\} \ (5)$$

where N is the total amount of samples.

The label for each sample is defined as:

$$L = \{(A_1, T_1, I_1), (A_2, T_2, T_3), \dots, (A_N, T_N, I_N)\} \ (6)$$

where L is the set of all samples with imposed pain artifacts and N is the total amount of samples. Each label contains the artifact, timing, and intensity.

The signal is imposed with the pain artifact by attenuating frequencies by the intensity at specific times, and its formula is:

$$K_n = STFT(S_n[A_c]])[A_b] + A_e * I_n * rect(\mathrm{t},\ T + A_d,\ T + A_d + A_t)(7)$$

where S_n is the original EEG sample. A_c returns the channels defined by the artifact. STFT() is the Short-Time Fourier transform function resulting in a time-frequency domain signal. From the time-frequency domain, the frequency amplitudes over the whole-time dimension at A_b frequencies are selected. t represents the time. The frequencies are attenuated by the effect A_e multiplied by the intensity I. This attenuation is only applied while the rectangular function returns 1, the rectangular function is defined as:

$$rect(t,a,b) = \begin{cases} 1, & if\ a \le t \le b \\ 0, & otherwise \end{cases} \quad (8)$$

The reconstructed signal is defined as:

$$F_n = ISTFT(K_n)\ (9)$$

Where ISTFT () is the Inverse Short-Time Fourier transformation function and S_n is the reconstructed signal in the time domain. The signal is reconstrued to the time domain via the Inverse Short-Time Fourier transform.

Figure 1 illustrates how a pain artifact affects the signal. The left signal shows the EEG recording at a single electrode. The right signal shows the reconstructed signal after a pain artifact has been imposed on it using the methodology explained in this section. At the 3 seconds mark, certain frequencies exhibit an increase, resulting in an overall enchantment in signal strength.
Figure 2 provides spectrograms before and after the introduction of a pain artifact. The modified spectrogram demonstrates heightened activity in the 5 Hz to 30 Hz range, lasting for 1 second, beginning at the 3 second mark.

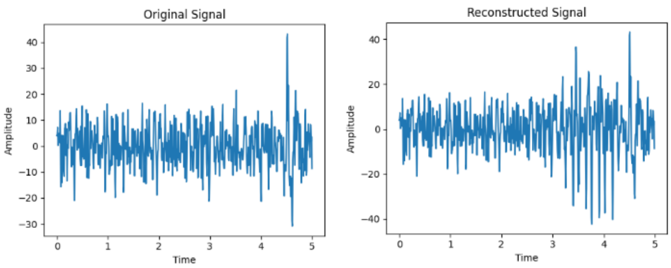

Figure 1 Example of a time-series imposed with a pain artifact.

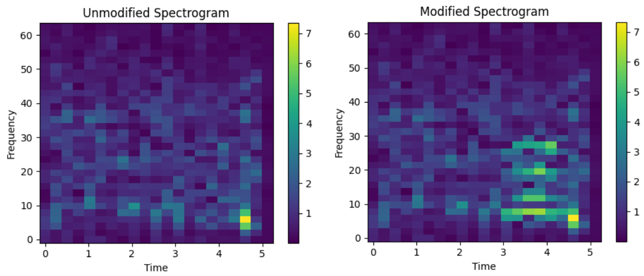

Figure 2 Example of a spectrogram imposed with a pain artifact.

The method described for imposing pain artifacts on EEG signal was implemented with custom Python scripts and files. To get real EEG data, EEG was recorded by the authors for 2 hours during regular daily activity while wearing an EEG recording device. Electrodes FP1, FP2, AF3, AF4, F3, F4, F7, F8, FC5, FC6, T3, T4, T5, T6, P3 and P4 were used and recorded at 125 Hz. The 2 hours of EEG data were split into 5 second segments and saved in files accessible to the Python scripts. To generate a sample with imposed pain artifact, a Python script loads a sample from the real EEG data. Then it chooses a pain artifact to impose and uses the algorithm explained earlier to impose pain artifacts on it.

A Convolutional Neural Network (CNN) model is used for classification and is implemented with the TensorFlow API in custom Python scripts. The CNN model is comprised of layers and starts with an input layer. The EEG samples were recorded with 16 channels at 125 Hz for 5 seconds. Thus, the shape of the input layer is 16 by 625. Following the input layer, 3 convolutional layers, each followed by an activation layer and a pooling layer. Following the third convolution, a flattened layer and a fully connected layer complete the CNN model. The model is compiled with a binary-crossentropy loss function and Adam-optimizer. The CNN model train to classify each sample into either no-pain or pain, hence a binary loss function. The goal being that the CNN could learn to classify real pain from no-pain because it has trained to classify fake pain from no-pain.

2 Results and Discussion

2.1 Results from Pain Detection CNN

EEG samples with real pain sensations were obtained by one of the authors of this article. EEG was recorded in 5 seconds samples and pain was induced by the author submerging a hand in icy water. This was done 20 times. 3 CNN models were trained on EEG samples, respectively 500, 1000 and 10000 sample sizes. Half the samples contained generated pain artifacts and the rest were regular EEG samples without pain. Every model was able to distinguish between no pain and pain with higher than 95% accuracy. All the models were fed the EEG samples with real pain. However, no correlation between real pain sensation and the output of the CNN algorithm was observed. This means that the CNN model did not find correlation between the imposed pain artifacts to real pain artifacts in EEG signals. Further improvements can be made with a CNN model created for EEG data.

3 Further Research

The algorithm for pain detection yielded unsuccessful classification of real pain signals. The CNN algorithm was trained on thousands of samples and could accurately classify the imposed pain from the EEG signals without imposed pain, but this did not translate to classification of real pain signals. Several factors may contribute to this. The chosen pain artifacts, for example reduction in alpha waves over the frontal cortex, may not correlate with acute pain and therefore calibrate the CNN with incorrect information. The real EEG data may not have been recorded with high enough resolution. Only 16 channels were recorded, a relatively small number compared to medical EEG equipment. The pain detection method can be improved in several ways for increasing the likelihood of success. For this study, only time-domain signals were analyzed by the CNN algorithm. More insight can be gained by including frequency and time-frequency domain signals into the analysis. The EEG was recorded with a lack of electrodes placed at the central regions of the scalp. This results in electrodes FCz and Cz not being included in the EEG recordings. Both electrodes have potential for pain detection [28]. With higher resolution EEG and more electrodes more information could be extracted from the brain activity. The EEG data with real pain sensations was recorded 20 times, each for 5 seconds. More EEG recordings with real pain sensations are needed to improve testability of the CNN model.

4 References

1. M. T. a. D. Kalnikaite, "A study of how Virtual Reality and Brain Computer Interface can manipulate the brain," in *The 5th International Conference on Software Engineering and Information Management (ICSIM)* , 2022.
2. Pinheiro, Eulália Silva dos Santos et al. “Electroencephalographic Patterns in Chronic Pain: A Systematic Review of the Literature.” PloS onevol. 11,2 e0149085. 25 Feb. 2016, doi: 10.1371/journal.pone.0149085.
3. A. Engel, C. Moll, I. Fried and G. Ojemann, "Invasive recordings from the human brain: Clinical insights and beyond," *Nature reviews Neuroscience,* no. 6, pp. 35-47, 2005.
4. S. JJ, K. DJ and W. JR, "Brain-computer interfaces in medicine," *Mayo Clin Proc,* vol. 87, no. 3, pp. 268-279, March 2012.
5. D. Plass-Oude Bos, "EEG-based Emotion Recognition," *The Influence of Visual and Auditory Stimuli,* vol. 56, pp. 1-17, 2006.

6. S. V. S. J. Bruno Bonnechère, "Chapter 39 - Rehabilitation," in *DHM and Posturography*, Academic Press, 2019, pp. 541-547,.
7. B. K. K. L. P. M.-G. a. R. B. Francesco Bellotti, "Assessment in and of serious games: an overview," *Adv. in Hum.-Comp. Int.*, 2013.
8. "Wikipedia," [Online]. Available: https://en.wikipedia.org/wiki/Fourier_transform. [Accessed 1 April 2023].
9. R. SN, C. DB, C. M, F. NB, F. H, G. S, K. FJ, M. JS, R. M, S. KA, S. XJ, S. B, S. MD, T. PR, U. T and V. K, "The revised International Association for the Study of Pain definition of pain: concepts, challenges, and compromises," *Pain,* vol. 161, no. 9, pp. 1976-1982, 1 September 2020.
10. H. SJ, W. AM, G. SJ and J. MP, "Acute Pain Management Pearls: A Focused Review for the Hospital Clinician," *Healthcare (Basel),* 11 December 2022.
11. S. R., "Causes and consequences of inadequate management of acute pain," *Pain Med,* vol. 11, no. 12, pp. 1859-1871, December 2010.
12. Y. Kong, L. Feng, H. Li, H. Cui, X. Xie, S. Xu and Y. Hu, "Low Back Pain Assessment Based on Alpha Oscillation Changes in Spontaneous Electroencephalogram," *Neural Plasticity and Neuropathic Pain,* 7 July 2021.
13. B. SF, L. S, R. J, M. K, S. J and K. M, "Does EEG activity during painful stimulation mirror more closely the noxious stimulus intensity or the subjective pain sensation?," *Somatosens Mot Res,* Vols. 3-4, pp. 192-198, December 2018.
14. V. Vijayakumar, "Automated Detection And Quantification Of Pain Using Electroencephalography," *Retrieved from the University of Minnesota Digital Conservancy,* 2018.
15. P. Panavaranan and Y. Wongsawat, "EEG-based pain estimation via fuzzy logic and polynomial kernel support vector machine," in *6th Biomedical Engineering International Conference*, 2013.
16. R. Reyes-Galaviz, O. Mendoza Montoya and J. Antelis, "Detection of Pain Caused by a Thermal Stimulus Using EEG and Machine Learning," in *Pattern Recognition*, 2022.
17. C. D, Z. H, K. PT, L. FL, N. SH, W. C, P. K. T. SY, Y. SY and G. C, "Scalp EEG-Based Pain Detection Using Convolutional Neural Network.," *IEEE Trans Neural Syst Rehabil Eng,* pp. 274-285, 2022.
18. S. Koyama, B. LeBlanc, K. Smith and e. al., "An Electroencephalography Bioassay for Preclinical Testing of Analgesic Efficacy," *Sci Rep,* vol. 8, 2018.
19. S. G, W. Z, O. D, D. L, W. J and C. ZS, "Detecting acute pain signals from human EEG," *J Neurosci Methods,* p. 347, 1 January 2021.
20. T. Yanagisawa, R. Fukuma, B. Seymour, M. Tanaka, K. Hosomi, O. Yamashita, H. Kishima, Y. Kamitani and Y. Saitoh, "BCI training to move a virtual hand reduces phantom limb pain," *Neurology,* vol. 95, no. 4, pp. 417-426, July 2020.
21. P. M, S. C and G. J, "Brain Rhythms of Pain," *Trends Cogn Sci,* vol. 21, no. 2, pp. 100-110, Febuary 2017.
22. P. L. A. A. A. e. a. Zis, "EEG Recordings as Biomarkers of Pain Perception: Where Do We Stand and Where to Go?," *Pain Ther,* pp. 369-380, 2022.
23. Z. Tayeb, R. Bose, A. Dragomir and e. al, "Decoding of Pain Perception using EEG Signals for a Real-Time Reflex System in Prostheses: A Case Study," *Sci Rep,* 2020.

24. L. Jingjing, Z. Jianwei, Z. Kan and Z. Jijian, "Predictive value of EEG-derived pain threshold index for acute postoperative pain in children," *Frontiers in Pediatrics,* vol. 10, 2022.

25. P. Leslie S. Prichep, P. E. Roy John, B. Bryant Howard, B. Henry Merkin and M. Emile M. Hiesiger, "Evaluation of the Pain Matrix Using EEG Source Localization: A Feasibility Study," *Pain Medicine,* vol. 12, no. 8, pp. 1241-1248.

26. S. C, O. DD, M. Y, B.-M. S and F. CE, "Clinical use of Electroencephalography in the Assessment of Acute Thermal Pain: A Narrative Review Based on Articles From 2009 to 2019," *Clin EEG Neurosci,* pp. 124-132, March 2022.

27. S. F. Bunk, S. Lautenbacher, J. Rüsseler, K. Müller, J. Schultz and M. Kunz, "Does EEG activity during painful stimulation mirror more closely the noxious stimulus intensity or the subjective pain sensation?," *Somatosensory & Motor Research,* vol. 35, no. 3-4, pp. 192-198, 2018.

28. I. Urits, D. Seifert, A. Seats and e. al, "reatment Strategies and Effective Management of Phantom Limb–Associated Pain," *Curr Pain Headache Rep,* vol. 23, no. 64, 2019.

29. P. ES, d. Q. FC, M. P, S. CL, d. N. MA, I. CH, S. M, N. S. DB, B. S, M. JG, S. KN and B. AF, "Electroencephalographic Patterns in Chronic Pain: A Systematic Review of the Literature," *PLoS One,* vol. 25, no. 11, p. 2, 2016.

30. S. E, Z. A, T. L, P. C and P. M, "Decoding an individual's sensitivity to pain from the multivariate analysis of EEG data," *Cereb Cortex,* vol. 22, no. 5, pp. 1118-1123, May 2012.