JOINT COMMON SPATIAL PATTERN AND SHORT-TIME FOURIER TRANSFORM WITH ATTENTION-BASED CONVOLUTIONAL NEURAL NETWORKS FOR BRAIN COMPUTER INTERFACE

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Choose an item.

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DEDICATION

This thesis is dedicated to my daughter, whom made me realized that if it is not me, then who will set the example for her; to my wife, who has always been present by my side all these time. It is also dedicated to my mother and family, who managed to raise everyone on her own despite not finishing school. Even now she tried her best to check in on me every now and then. This is for you, Umi. Last but not least, to my late dad. I remember him saying that he wanted to continue his studies but could not achieve his dreams due to health and work reasons.

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ABSTRACT

Motor imagery on electroencephalogram (EEG) signals is widely used in brain-computer interface (BCI) systems with many exciting applications. There are three major types of filtering for EEG signals- temporal, spectral, and spatial filtering. Spatial filtering using Common Spatial Pattern (CSP) is an established method of processing EEG signals as classifier inputs. With the recent advent of deep learning, many deep learning classifiers have been adopted, including Recurrent Neural Network (RNN) and Convolutional Neural Networks (CNNs). In the early adoption of CNN to solve BCI based on EEG, the raw EEG signal is fed to CNN for classification. However, in the recent trend, various representations of CNN exist for BCI EEG classification, either spatial or temporal only, or a combination of both, or other similar features to enhance the signal further. Also, there exist multiple implementations of attention networks for BCI EEG classification. However, most of the existing work does not utilize a good filter and spatial or temporal representation by using attention networks. This study develops a framework using CSP and Short-Time Fourier Transform (STFT) as well as Attention Convolutional Neural Network (CSP-STFT-attCNN) for EEG BCI classification. The features from CSP are translated into the spatial domain using STFT as input to attention-based CNN as the classifier. The first step is to preprocess the raw EEG signals, perform channel selection, separate them into train and test data, and apply CSP-STFT. Then, the model architecture to train with the data is defined. This framework uses attention-based CNNs to classify the collected spatial images across different test subjects. Finally, the performance of the CSP-STFT-attCNN has been validated on two BCI benchmark datasets 1) Competition III dataset IVa 2) Competition IV dataset I. The proposed CSP-STFT-attCNN has proved that the framework based on CSP-STFT as feature extractor and Attention-CNNs offers a promising result; the classifier achieved better performance in terms of classification accuracy, averaging 80% across all five subjects for Competition III dataset IVa. The precision and recall are excellent too, ranging around 0.8-0.9. Nonetheless CSP-STFT-attCNN did not perform as well with the other dataset, hence the reasons are explored further. In general, the proposed CSP-STFT-attCNN can offer richer joint spatiotemporal features as inputs to classifiers, whereas using an Attention-CNN classifier improves upon the earlier problems suffered by CNNs.

ABSTRAK

Pengimejan motor pada isyarat elektroencephalograf (EEG) telahpun digunakan secara meluas dalam sistem *Brain Computer Interfaces* (BCI) dengan banyak aplikasi yang menarik. Terdapat tiga jenis teknik penapisan untuk isyarat EEG-tapisan secara temporal, spektrum dan spatial. Penapisan spatial menggunakan Corak Spatial Biasa (CSP) ialah kaedah yang sering digunakan untuk memproses isyarat EEG sebagai sumber kepada model pengelasan untuk dikelaskan mengikut label yang betul. Dengan kemunculan teknik *deep learning*, banyak model pengelasan jenis *deep learning* telah diterima pakai, termasuk rangkaian neural berulang (RNN) dan rangkaian neural berlingkar (CNN). Ketika kajian menggunakan CNN untuk aktiviti BCI berdasarkan EEG masih baru, kebiasaan yang diguna pakai ialah untuk menyalurkan isyarat EEG secara terus kepada CNN. Pada masa kini, pelbagai bentuk pemprosesan isyarat kepada CNN telah diwujudkan untuk tujuan pengelasan BCI EEG, tidak mengira jenis spatial, temporal mahupun penggabungan kedua-duanya atau lebih. Di samping itu, terdapat juga pelbagai kajian yang menggunakan rangkaian jenis perhatian untuk pengelasan BCI EEG. Namun begitu, kebanyakan kajian sedia ada tidak menggunakan penapis isyarat yang baik. Kajian ini membangunkan CNN bersama mekanisma perhatian dan digabungkan dengan algoritma CSP-STFT (CSP-STFT-attCNN) untuk klasifikasi EEG BCI. Isyarat EEG ditapis, pemilihan saluran isyarat penting akan dilakukan sebelum memisahkan data kepada dua bahagian untuk proses melatih dan menguji, dan mengaplikasikan CSP-STFT. Ciri-ciri penting daripada CSP diterjemahkan ke dalam bentuk gabungan spatial dan temporal menggunakan *Short-Time Fourier Transform* (STFT) sebelum disalurkan kepada CNN berasaskan mekanisma perhatian. Kemudian, model pengelasan tersebut akan dilatih untuk mengelaskan imej spectrum. Akhir sekali, prestasi CSP-STFT-attCNN disahkan semula pada dua set data penanda aras BCI 1) Pertandingan III set data IVa 2) Pertandingan IV set data I. Cadangan CSP-STFT-attCNN menawarkan hasil yang memberangsangkan dengan purata ketepatan 80% untuk salah satu set data. Secara umum, CSP-STFT-attCNN yang dicadangkan menawarkan ciri berkembar yang lebih kaya sebagai sumber kepada model pengelas gabungan mekanisma perhatian dan CNN yang menambah baik masalah terdahulu yang dialami oleh CNN.

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LIST OF ABBREVIATIONS

ANN	-	Artificial Neural Network
BCI	-	Brain Computer Interface
CNNs	-	Convolutional Neural Networks
CSP	-	Common Spatial Pattern
EEG	-	Electroencephalogram
ELM	-	Extreme Learning Machine
LDA	-	Linear Discriminant Analysis
RNNs	-	Recurrent Neural Networks
STFT	-	Short-Time Fourier Transform
UTM	-	Universiti Teknologi Malaysia

CHAPTER 1

INTRODUCTION

1.1 Problem Background

The BCI, in general, is a non-invasive computing system capable of communicating with the brain, limited only to the signals directly coming from the central nervous system instead of the ones transmitted into the periphery of nerves and muscles. Moreover, it also analyses and transforms the brain signals into interpretable commands that can be further relayed to an actuator or output device in order to carry out a specified action precisely. By and large, a BCI system comprises of four major components, namely the signal acquisition device, feature extraction, feature translation and actuator.

The brain signals are first acquired from the electrodes that are firmly hooked to their predetermined positions on a subject's scalp. An EEG device that is connected to these electrodes would then be utilized to record the electrical activity by measuring the voltage fluctuations, which is the product of ionic current found within the brain neurons. This signal acquisition undertaking would go on for a period of time, usually over a few trials to ensure consistency and to obtain the representative activity of the brain. EEG signals extracted can be derivatively extracted into event-related potential (ERP) or evoked potential (EP). EP is particularly an electrical potential recorded from a specific region of the central nervous system in response to an external stimuli such as light or touch.

On the other hand, ERP focuses on rhythmic brain response as a consequence of a distinct sensory, cognitive or motor event. EEG has been the go-to method in medical field as a diagnostic test for epilepsy, brain tumour, stroke and sleep disorders among others. It has also been prominently used in researches involving many branches of subjects concerning the central nervous system and cognitive abilities such as neuroscience, cognitive science, cognitive psychology, neurolinguistics, neuropsychology and many more. By amalgamation of behaviour and ERPs measures, (Fu et al., 2019) managed to investigate the effect of price deception on consumers' purchase decision. Another study used ERP data to compare performances of younger and older adults in multiple identity tracking tasks (Pehlivanoglu, Duarte, & Verhaeghen, 2020). In a similar fashion, ERP data are collected from patients struggling with depression against a control group during source memory retrieval activity (Barrick & Dillon, 2018).

The motor imagery signals, having been widely used in BCI systems as part of neuroimaging and rehabilitation, are considered under the ERP derivative of EEG. In the motor imagery paradigm, by having the user to imagine the execution of a specific movement with a designated limb, the command is encoded by altering the rhythmic activity in locations concerning the sensorimotor cortex that would typically correspond to this limb (Lotze & Halsband, 2006). After recording the signal, the BCI system would proceed to decode the intended command correctly. Nonetheless a significant problem in EEG-based BCI systems is the limited quality and resolution of the signal due to volume conduction effects, a low signal-to-noise ratio, and the non-stationary nature of EEG (Samek, Vidaurre, Müller, & Kawanabe, 2012). In order to improve the quality and get a better motor imagery signal, the noise and artefact signals should be eliminated through filtering process. For the EEG signals, there are a multitude of methods for filtering them such as temporal, spectral, and spatial filtering.

In comparison to temporal and spectral filtering, it has been established that spatial filtering can produce a better representation of the signal (Burle et al., 2015). Spatial filtering is a type of filtering that combines the EEG signal coming in from multiple electrodes to improve the signal-to-noise ratio compared to simply taking in the EEG signal from signal electrodes. The recorded signal at one particular electrode does not only reflect neural voltage fluctuations underneath the electrode, but also captures the distance between current sources through volume conduction effects. Spatial filters are useful for discriminating different classes of EEG signals such as those corresponding to motor activities (Yong, Ward, & Birch, 2008b). It is undeniable that spatial filtering for EEG feature extraction and classification is an important tool in the brain–computer interface. Diving in further, the most widely used spatial filtering method in motor imagery for BCI applications is the common spatial pattern (Jamaloo & Mikaili, 2015; Samek, Kawanabe, & Muller, 2014).

Common spatial pattern (CSP) algorithm is commonly used in processing motor imagery EEG signals because it can differentiate the mental states induced by motor imagery (Samek et al., 2014). However, in the CSP algorithm, the estimation of the covariance matrix for the two classes may not represent the true representation of each sensor node from EEG, so the estimation may create a spurious relationship between EEG sensor nodes. Therefore, many strategies have been proposed to improve CSP performance (Samek et al., 2014). In addition to that, there are also many modifications to the original CSP such as analytical CSP. Some studies propose combining CSP with other transform methods to further boost the signal representation such as using Short-Time Fourier Transform to obtain the joint time-frequency features and rendering them as two-dimensional spectral images.

With the emergence of deep learning, many studies have employed different deep learning models in many applications and achieved high performance. For instance, convolutional neural networks (CNNs) are instrumental in extracting local and spatial features and patterns directly from raw data such as images (Altaheri et al., 2019), videos (Al-Hammadi, Muhammad, Abdul, Alsulaiman, & Hossain, 2020), and speech (Hossain & Muhammad, 2018). Recurrent neural networks (RNNs) can extract temporal features and patterns from time-series data, making them useful in video and speech applications (Bae, Choi, & Kim, 2016; Nguyen & Pernkopf, 2018). Transformers, which are gaining more traction recently, can process sequential data without handling them in recursion, which is fantastic for applications such as machine translation. Inspired by the high performance of deep learning techniques in various areas, several authors utilized deep learning methods to classify EEG signals such as CNNs (Amin, Alsulaiman, Muhammad, Mekhtiche, & Shamim Hossain, 2019; Amin, Muhammad, Abdul, Bencherif, & Alsulaiman, 2020), RNNs (Ma, Qiu, Du, Xing, & He, 2018; Rashid et al., 2020), and deep belief networks (DBN) (Cheng et al., 2020). However, there is still more work to ensure that the performance of current deep learning techniques applied to EEG MI classification is comparable to other fields like image and speech recognition.

1.2 Problem Statement

Finding a good motor imagery EEG signal is quite challenging. One of the prominent methods to identify motor imagery features is to use the CSP algorithm. Nevertheless, the CSP algorithm on its own is very sensitive to outliers or noise that is introduced from external sources, which would degrade the processed signals (Yong, Ward, & Birch, 2008a). Consequently, using the CSP algorithm has its own difficulties when estimating the class of covariance matrices, which may be negatively influenced by EEG-measurement artefacts such as subject movements or loose electrodes, such that CSP assumes all channels to be related to one another even when only noise relationships are evident. Although CSP has been extended into various forms, the main disadvantage of CSP is the assumption that noisy channels are active. These active channels may introduce a spurious relationship between channels when CSP estimates the covariance matrix.

On the other hand, another way to process the EEG signals is to take the time and frequency features only. This has been proven to work with techniques such as Fourier Transform and Wavelet Transform. However, while these methods work just fine in achieving their objectives, using them alone will not improve the BCI system in overall.

CNNs have convolutional layers that can extract specific features from the image, outperforming the basic neural networks. This is why CNNs have mainly been utilized for image classification. Nonetheless, while CNNs are being introduced in motor imagery classification, CNNs suffer from the loss of salient features during training, causing the spatial invariant problem that affects the performance. In addition to that, CNNs are much slower as the application of the convolutional layers can only focus on one distinctive feature at a time. Attention mechanism has been able to mimic brain cognitive process and is majorly used for machine translation, beginning to phase

RNN and LSTM out of the way in many natural language applications. Recently attention has also been used extensively in computer vision. It is discovered that attention can learn just as well if not even better than CNNs when extracting features from images to perform classification.

In summary, there are various approaches to improve the overall BCI system utilizing CSP algorithms on the extraction part such as integration with STFT and classifier with attention mechanism applied together with CNNs to boost the classification. It is important to determine the right combination of CSP and STFT and process it as inputs to Attention-CNNs, as well as tuning the Attention-CNNs so that it will be able to take in the features and classify them well. However, an improper feature extraction process could further reduce the quality of the image representation and eliminate important information from the EEG signal. Besides, the wrong arrangement and definition in the model building stage will also hinder the model from learning better.

1.3 Research Objective

The objective of this study is to introduce a novel combination of motor imagery BCI systems that combines CSP, STFT, and deep learning algorithms altogether. The specific objectives of this study are outlined below:

i) To develop a combination method of CSP and STFT to enhance the existing CSP algorithm.
ii) To develop the attention-based CNNs for BCI motor imagery classification on i)
iii) To validate the proposed method on the existing benchmark dataset: Dataset IVa BCI Competition III and Dataset I BCI Competition IV.

1.4 Research Scope and Limitation

The scope and limitation of this research are listed below:

i) This research uses two-class motor imageries only as the benchmark data, namely the BCI competition III dataset IVa and the BCI competition IV dataset I.

ii) The proposed improvement was only validated with the existing CSP algorithm.

iii) The proposed system or methodology was tested in a simulated set-up using Python virtual environment meant for development and was not done in real-time.

1.5 Thesis Contribution

The contributions of this research are as follows:

i) An introduction of STFT to complement CSP as a feature extraction process for EEG signals to obtain better motor imagery rendering.

ii) Proposed CNNs with Attention mechanism to combat the spatial invariance problem suffered by CNNs in dealing with 2D imagery.

iii) The application of a novel methodology for BCI system, namely the integrated CSP-STFT with Attention-CNN classifier scheme. The proposed scheme is configured to run end-to-end with the CSP-STFT adjusted to obtain better signal representation and the Attention-CNN model adjusted to maximise the learning of the motor imagery.

1.6 Thesis Outline

This thesis is organized into five chapters. Typically the first chapter will discuss on problem background, present the problem statement, project scope and expected contribution as an outcome of the study.

In Chapter 2, a literature review on BCI, EEG signals, the CSP algorithm, the STFT algorithm, classifier methods, CNNs and attention mechanisms methods for the EEG motor imagery signal is presented. All points are to be reviewed with the related theory to this study being highlighted.

In Chapter 3, the proposed methodology is presented. In this chapter, the dataset used is elaborated on. In addition to that, a brief outline of the proposed BCI system, the dataset, pre-processing, feature extraction, classification, and performance evaluation is discussed.

In Chapter 4, the results and discussion are presented, focusing on the results of experimental research on comparative performance analysis and evaluation. This chapter presents an evaluation of the test to assess system performance. The novel BCI system is compared and evaluated using three parameter tests, i.e., accuracy, precision and recall, with the results outlined at the end of this chapter.

In Chapter 5, the conclusions of the study and future works are discussed including the recommendations, improvements, and/or validations for possible future works.

REFERENCES

Abdulkader, S. N., Atia, A., & Mostafa, M. S. M. (2015). Brain computer interfacing: Applications and challenges. *Egyptian Informatics Journal*, *16*(2), 213–230.

Abibullaev, B., An, J., Lee, S. H., & Moon, J. il. (2017). Design and evaluation of action observation and motor imagery based BCIs using Near-Infrared Spectroscopy. *Measurement: Journal of the International Measurement Confederation*, *98*, 250–261. https://doi.org/10.1016/j.measurement.2016.12.001

Aghaei, A. S., Mahanta, M. S., & Plataniotis, K. N. (2013). Separable common spatio-spectral pattern algorithm for classification of EEG signals. *ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings*, 988–992. https://doi.org/10.1109/ICASSP.2013.6637797

Ahmadi, A., Jafari, R., & Hart Jr., J. (2011). Light-weight single trial EEG signal processing algorithms: computational profiling for low power design. *Conference Proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual Conference*, *2011*, 4426–4430.

Albalawi, H., & Song, X. (2012). A study of kernel CSP-based motor imagery brain computer interface classification. In *2012 IEEE Signal Processing in Medicine and Biology Symposium, SPMB 2012*.

Albawi, S., Mohammed, T. A., & Al-Zawi, S. (2018). Understanding of a convolutional neural network. *Proceedings of 2017 International Conference on Engineering and Technology, ICET 2017*, *2018-January*, 1–6. Institute of Electrical and Electronics Engineers Inc. https://doi.org/10.1109/ICEngTechnol.2017.8308186

Alhagry, S., Aly, A., & El-Khoribi, R. (2017). Emotion Recognition based on EEG using LSTM Recurrent Neural Network. *International Journal of Advanced Computer Science and Applications*, *8*. https://doi.org/10.14569/IJACSA.2017.081046

Al-Hammadi, M., Muhammad, G., Abdul, W., Alsulaiman, M., & Hossain, M. S. (2020). Hand Gesture Recognition Using 3D-CNN Model. *IEEE Consumer Electronics Magazine*, *9*, 95–101. https://doi.org/10.1109/MCE.2019.2941464

Al-Saegh, A., Dawwd, S. A., & Abdul-Jabbar, J. M. (2021, January 1). Deep learning for motor imagery EEG-based classification: A review. *Biomedical Signal Processing and Control*, Vol. 63. Elsevier Ltd. https://doi.org/10.1016/j.bspc.2020.102172

Alotaiby, T., El-Samie, F. E. A., Alshebeili, S. A., & Ahmad, I. (2015). A review of channel selection algorithms for EEG signal processing. *Eurasip Journal on Advances in Signal Processing*, *2015*(1).

Altaheri, H., Alsulaiman, M., Muhammad, G., Amin, S., Bencherif, M., & Amine, mohamed amine. (2019). Date Fruit Dataset for Intelligent Harvesting. *Data in Brief*, *26*, 104514. https://doi.org/10.1016/j.dib.2019.104514

Amin Morid, M., Borjali, A., & Fiol, G. del. (n.d.). *A scoping review of transfer learning research on medical image analysis using ImageNet*.

Amin, S. U., Alsulaiman, M., Muhammad, G., Mekhtiche, M. A., & Shamim Hossain, M. (2019). Deep Learning for EEG motor imagery classification based on multi-layer CNNs feature fusion. *Future Generation Computer Systems*, *101*, 542–554.

Amin, S. U., Muhammad, G., Abdul, W., Bencherif, M., & Alsulaiman, M. (2020). Multi-CNN Feature Fusion for Efficient EEG Classification. *2020 IEEE International Conference on Multimedia Expo Workshops (ICMEW)*, 1–6. https://doi.org/10.1109/ICMEW46912.2020.9106021

Andersen, L. M., Pfeiffer, C., Ruffieux, S., Riaz, B., Winkler, D., Schneiderman, J. F., & Lundqvist, D. (2020). On-scalp MEG SQUIDs are sensitive to early somatosensory activity unseen by conventional MEG. *NeuroImage*, *221*. https://doi.org/10.1016/j.neuroimage.2020.117157

Annaby, M. H., Said, M. H., Eldeib, A. M., & Rushdi, M. A. (2021). EEG-based motor imagery classification using digraph Fourier transforms and extreme learning machines. *Biomedical Signal Processing and Control*, *69*. https://doi.org/10.1016/j.bspc.2021.102831

Arns, M., Cerquera, A., Gutiérrez, R. M., Hasselman, F., & Freund, J. A. (2014). Non-linear EEG analyses predict non-response to rTMS treatment in major depressive disorder. *Clinical Neurophysiology*, *125*(7), 1392–1399. https://doi.org/10.1016/j.clinph.2013.11.022

Arvaneh, M., Guan, C., Ang, K. K., & Quek, C. (2011). Optimizing the channel selection and classification accuracy in EEG-based BCI. *IEEE Transactions on Biomedical Engineering*, *58*(6), 1865–1873.

Arvaneh, M., Guan, C., Ang, K. K., & Quek, C. (2012). Robust EEG channel selection across sessions in brain-computer interface involving stroke patients. In *Proceedings of the International Joint Conference on Neural Networks*.

Arvaneh, M., Guan, C., & Chai Quek. (2013). EEG Data Space Adaptation to Reduce Intersession Nonstationary in Brain-Computer Interface. *Journal of Neural Computation*, *25*, 1–26.

Astigarraga, A., Arruti, A., Muguerza, J., Santana, R., Martin, J. I., & Sierra, B. (2016). User Adapted Motor-Imaginary Brain-Computer Interface by means of EEG Channel Selection Based on Estimation of Distributed Algorithms. *Mathematical Problems in Engineering*, *2016*.

Aydin, E. A. (2020). Subject-Specific feature selection for near infrared spectroscopy based brain-computer interfaces. *Computer Methods and Programs in Biomedicine*, *195*. https://doi.org/10.1016/j.cmpb.2020.105535

Babiloni, C., Pizzella, V., DelGratta, C., Ferretti, A., & Romani, G.-L. (2009). Fundamentals of Electroencefalography, Magnetoencefalography, and Functional Magnetic Resonance Imaging. *International Review of Neurobiology*, *86*, 67–80. https://doi.org/10.1016/S0074-7742(09)86005-4

Bae, S. H., Choi, I., & Kim, N. S. (2016). *Detection and Classification of Acoustic Scenes and Events*.

Bahador, N., & Kortelainen, J. (2022). Deep learning-based classification of multichannel bio-signals using directedness transfer learning. *Biomedical Signal Processing and Control*, *72*. https://doi.org/10.1016/j.bspc.2021.103300

Bahdanau, D., Cho, K., & Bengio, Y. (2014). *Neural Machine Translation by Jointly Learning to Align and Translate*. Retrieved from http://arxiv.org/abs/1409.0473

Baillet, S., Mosher, J. C., & Leahy, R. M. (2001). Electromagnetic brain mapping. *IEEE Signal Processing Magazine*, *18*(6), 14–30. https://doi.org/10.1109/79.962275

Bamdadian, A., Guan, C., Ang, K. K., & Xu, J. (2013). Improving session-to-session transfer performance of motor imagery-based BCI using adaptive extreme learning machine. In *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS* (pp. 2188–2191).

Barachant, A., Bonnet, S., Congedo, M., & Jutten, C. (2012). Multiclass braincomputer interface classification by Riemannian geometry. *IEEE Transactions on Biomedical Engineering*, *59*(4), 920–928.

Barrick, E. M., & Dillon, D. G. (2018). An ERP study of multidimensional source retrieval in depression. *Biological Psychology*, *132*, 176–191. https://doi.org/10.1016/j.biopsycho.2018.01.001

Blankertz, B., Dornhege, G., Krauledat, M., Müller, K. R., & Curio, G. (2007). The non-invasive Berlin Brain-Computer Interface: Fast acquisition of effective performance in untrained subjects. *NeuroImage*, *37*(2), 539–550. https://doi.org/https://doi.org/10.1016/j.neuroimage.2007.01.051

Blankertz, B., Kawanabe, M., Tomioka, R., Hohlefeld, F., Nikulin, V., & Müller, K.R. (2007). Invariant common spatial patterns: Alleviating nonstationarities in brain-computer interfacing. *Advances in Neural Information Processing Systems*, 1–8.

Blankertz, B., Tomioka, R., Lemm, S., Kawanabe, M., & Müller, K. R. (2008). Optimizing spatial filters for robust EEG single-trial analysis. *IEEE Signal Processing Magazine*, *25*(1), 41–56. https://doi.org/10.1109/MSP.2008.4408441

Brigham, K., & Kumar, B. V. K. V. (2010). Subject identification from Electroencephalogram (EEG) signals during imagined speech. In *IEEE 4th International Conference on Biometrics: Theory, Applications and Systems, BTAS 2010*.

Burle, B., Spieser, L., Roger, C., Casini, L., Hasbroucq, T., & Vidal, F. (2015). Spatial and temporal resolutions of EEG: Is it really black and white? A scalp current density view. *International Journal of Psychophysiology*, *97*(3), 210–220.

Chaudhary, S., Taran, S., Bajaj, V., & Sengur, A. (2019). Convolutional Neural Network Based Approach Towards Motor Imagery Tasks EEG Signals Classification. *IEEE Sensors Journal*, *19*(12), 4494–4500. https://doi.org/10.1109/JSEN.2019.2899645

Cheng, L., Li, D., Yu, G., Zhang, Z., Li, X., & Yu, S. (2020). A Motor Imagery EEG Feature Extraction Method Based on Energy Principal Component Analysis and Deep Belief Networks. *IEEE Access*, *8*, 21453–21472. https://doi.org/10.1109/ACCESS.2020.2969054

Chin, Z. Y., Ang, K. K., Wang, C., & Guan, C. (2014). Discriminative channel addition and reduction for filter bank common spatial pattern in motor imagery BCI. In *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC 2014* (pp. 1310–1313).

Christopher deCharms, R. (2008). Applications of real-time fMRI. *Nature Reviews Neuroscience*, *9*(9), 720–729. https://doi.org/10.1038/nrn2414

Corsi, M. C., Chavez, M., Schwartz, D., George, N., Hugueville, L., Kahn, A. E., … de Vico Fallani, F. (2020). Functional disconnection of associative cortical areas predicts performance during BCI training. *NeuroImage*, *209*. https://doi.org/10.1016/j.neuroimage.2019.116500

Coyle, S., Ward, T., Markham, C., & Mcdarby, G. (2004). On the suitability of near-infrared (NIR) systems for next-generation brain-computer interfaces. *Physiological Measurement*, *25*, 815–822. https://doi.org/10.1088/0967-3334/25/4/003

Daud, S. S., & Sudirman, R. (2015). Butterworth Bandpass and Stationary Wavelet Transform Filter Comparison for Electroencephalography Signal. In *Proceedings - International Conference on Intelligent Systems, Modelling and Simulation, ISMS* (Vol. 2015–Octob, pp. 123–126).

deCharms, C., Christoff, K., Glover, G., Pauly, J., Whitfield, S., & Gabrieli, J. (2004). Learned regulation of spatially localized brain activation using real-time fMRI.

Duan, L., Bao, M., Miao, J., Xu, Y., & Chen, J. (2016). Classification Based on Multilayer Extreme Learning Machine for Motor Imagery Task from EEG Signals. In *Procedia Computer Science* (Vol. 88, pp. 176–184).

Fauzi, H., Azzam, M., Shapiai, M. I., Kyoso, M., Khairuddin, U., & Komura, T. (2019). Energy extraction method for EEG channel selection. *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, *17*, 2561. https://doi.org/10.12928/telkomnika.v17i5.12805

Fauzi, H., Shapiai, M. I., & Khairuddin, U. (2020). Transfer Learning of BCI Using CUR Algorithm. *Journal of Signal Processing Systems*, *92*(1), 109–121. https://doi.org/10.1007/s11265-019-1440-9

Fauzi, H., Shapiai, M. I., Setiawan, N. A., Jaafar, J., & Mustafa, M. (2017). Channel selection for common spatial pattern Based on energy calculation of motor imagery EEG signal. In *2017 International Conference on Control, Electronics, Renewable Energy and Communications (ICCREC)* (pp. 33–39). IEEE.

Fauzi, H., Shapiai, M. I., Yusof, R., Remijn, G. B., Setiawan, N. A., & Ibrahim, Z. (2017). *The design of spatial selection using CUR decomposition to improve common spatial pattern for multi-trial EEG classification*. *Communications in Computer and Information Science* (Vol. 751). Melaka: Springer.

Fazli, S., Danóczy, M., & Schelldorfer, J. (2011). l1-penalized Linear Mixed-Effects Models for high dimensional data with application to BCI. *NeuroImage*.

Fonseca, C., Cunha, J. P., Martins, R., Ferreira, V., Sa, J., Barbosa, M., & Silva, A. (2007). A Novel Dry Active Electrode for EEG Recording. *Biomedical Engineering, IEEE Transactions On*, *54*, 162–165. https://doi.org/10.1109/TBME.2006.884649

Fu, H., Ma, H., Bian, J., Wang, C., Zhou, J., & Ma, Q. (2019). Don't trick me: An event-related potentials investigation of how price deception decreases consumer purchase intention. *Neuroscience Letters*, *713*. https://doi.org/10.1016/j.neulet.2019.134522

Geng, S., Zhou, W., Yuan, Q., Cai, D., & Zeng, Y. (2011). EEG non-linear feature extraction using correlation dimension and Hurst exponent. *Neurological Research*, *33*(9), 908–912.

Goldberger, A., Amaral, L., Glass, L., Havlin, S., Hausdorg, J., Ivanov, P., … Stanley, H. (2000). PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. *PhysioNet*, *101*.

Greaves, A. S. (2015). *Classification of EEG with Recurrent Neural Networks*.

Han, Y., Wang, B., Luo, J., Li, L., & Li, X. (2022). A classification method for EEG motor imagery signals based on parallel convolutional neural network. *Biomedical Signal Processing and Control*, *71*. https://doi.org/10.1016/j.bspc.2021.103190

Hlawatsch, F., & Auger, F. (2008). *Time-Frequency Analysis: Concepts and Methods* (1st ed.). ISTE.

Hossain, M. S., & Muhammad, G. (2018). Emotion-Aware Connected Healthcare Big Data Towards 5G. *IEEE Internet of Things Journal*, *5*(4), 2399–2406. https://doi.org/10.1109/JIOT.2017.2772959

Howard, A. G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., & Andreetto, M. (n.d.). *MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications*.

Hou, Y., Chen, T., Lun, X., & Wang, F. (2022). A novel method for classification of multi-class motor imagery tasks based on feature fusion. *Neuroscience Research*, *176*, 40–48. https://doi.org/10.1016/j.neures.2021.09.002

Jain, A., Kim, I., & Gluckman, B. J. (2011). Low cost electroencephalographic acquisition amplifier to serve as teaching and research tool. *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 1888–1891. https://doi.org/10.1109/IEMBS.2011.6090535

Jamaloo, F., & Mikaili, M. (2015). Assessment of distinction sensitive learning vector quantization weighted common spatial pattern features for EEG classification in brain computer interface. In *ICEE 2015 - Proceedings of the 23rd Iranian Conference on Electrical Engineering* (Vol. 10, pp. 44–49).

Janapati, R., Dalal, V., & Sengupta, R. (2021). Advances in modern EEG-BCI signal processing: A review. *Materials Today: Proceedings*. https://doi.org/10.1016/j.matpr.2021.06.409

Jetley, S., Lord, N. A., Lee, N., & Torr, P. H. S. (2018). *Learn To Pay Attention*. Retrieved from http://arxiv.org/abs/1804.02391

Kennan, R. P., Horovitz, S. G., Maki, A., Yamashita, Y., Koizumi, H., & Gore, J. C. (2002). Simultaneous Recording of Event-Related Auditory Oddball Response Using Transcranial Near Infrared Optical Topography and Surface EEG. *NeuroImage*, *16*(3, Part A), 587–592. https://doi.org/https://doi.org/10.1006/nimg.2002.1060

Khosla, A., Khandnor, P., & Chand, T. (2020, April 1). A comparative analysis of signal processing and classification methods for different applications based on EEG signals. *Biocybernetics and Biomedical Engineering*, Vol. 40, pp. 649–690. Elsevier Sp. z o.o. https://doi.org/10.1016/j.bbe.2020.02.002

Klem, G. H., Lüders, H., Jasper, H. H., & Elger, C. E. (1999). The ten-twenty electrode system of the International Federation. The International Federation of Clinical Neurophysiology. *Electroencephalography and Clinical Neurophysiology. Supplement*, *52*, 3–6.

Koles, Z. J., Lazar, M. S., & Zhou, S. Z. (1990). Spatial patterns underlying population differences in the background EEG. *Brain Topography*, *2*(4), 275–284.

Koo, B., Lee, H. G., Nam, Y., Kang, H., Koh, C. S., Shin, H. C., & Choi, S. (2015). A hybrid NIRS-EEG system for self-paced brain computer interface with online motor imagery. *Journal of Neuroscience Methods*, *244*, 26–32.

Leach, W. M. (1994). Fundamentals of low-noise analog circuit design. *Proceedings of the IEEE*, *82*(10), 1515–1538. https://doi.org/10.1109/5.326411

Leamy, D. J., Kocijan, J., Domijan, K., Duffin, J., Roche, R. A. P., Commins, S., … Ward, T. E. (2014). An exploration of EEG features during recovery following stroke – implications for BCI-mediated neurorehabilitation therapy, 1–16.

Lee, M.-H., Kwon, O.-Y., Kim, Y.-J., Kim, H.-K., Lee, Y.-E., Williamson, J., … Lee, S.-W. (2019). EEG dataset and OpenBMI toolbox for three BCI paradigms: an investigation into BCI illiteracy. *GigaScience*, *8*. https://doi.org/10.1093/gigascience/giz002

Lewandowski, C. M., Co-investigator, N., & Lewandowski, C. M. (2015). *Towards Practical Brain-Computer Interfaces: Bridging the Gap from Research to Real World Applications*. *The effects of brief mindfulness intervention on acute pain experience: An examination of individual difference* (Vol. 1).

Li, H., Ding, M., Zhang, R., & Xiu, C. (2022). Motor imagery EEG classification algorithm based on CNN-LSTM feature fusion network. *Biomedical Signal Processing and Control*, *72*. https://doi.org/10.1016/j.bspc.2021.103342

Li, J., Wang, Y., Zhang, L., & Jung, T. P. (2012). Combining ERPs and EEG spectral features for decoding intended movement direction. In *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS* (pp. 1769–1772).

Li, K. G., Shapiai, M. I., Adam, A., & Ibrahim, Z. (2017). Feature scaling for EEG human concentration using particle swarm optimization. *Proceedings of 2016 8th International Conference on Information Technology and Electrical Engineering: Empowering Technology for Better Future, ICITEE 2016*. https://doi.org/10.1109/ICITEED.2016.7863292

Lin, X., Sai, L., & Yuan, Z. (2018). Detecting Concealed Information with Fused Electroencephalography and Functional Near-infrared Spectroscopy. *Neuroscience*, *386*, 284–294. https://doi.org/10.1016/j.neuroscience.2018.06.049

Lotte, F., Congedo, M., Lécuyer, A., Lamarche, F., & Arnaldi, B. (2007). A review of classification algorithms for EEG-based brain–computer interfaces. *Journal of Neural Engineering*, *4*(2), R1–R13.

Lotze, M., & Halsband, U. (2006). Motor imagery. *Journal of Physiology Paris*, *99*(4– 6), 386–395.

Lu, H., Eng, H. L., Guan, C., Plataniotis, K. N., & Venetsanopoulos, A. N. (2010). Regularized common spatial pattern with aggregation for EEG Classification in small-sample setting. *IEEE Transactions on Biomedical Engineering*, *57*(12), 2936–2946.

Lu, H., Plataniotis, K. N., & Venetsanopoulos, A. N. (2009). Regularized common spatial patterns with generic learning for EEG signal classification. In *Proceedings of the 31st Annual International Conference of the IEEE Engineering in Medicine and Biology Society: Engineering the Future of Biomedicine, EMBC 2009* (pp. 6599–6602).

Luong, M.-T., Pham, H., & Manning, C. D. (2015). *Effective Approaches to Attention-based Neural Machine Translation*. Retrieved from http://arxiv.org/abs/1508.04025

Ma, X., Qiu, S., Du, C., Xing, J., & He, H. (2018). Improving EEG-Based Motor Imagery Classification via Spatial and Temporal Recurrent Neural Networks. *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 1903–1906. https://doi.org/10.1109/EMBC.2018.8512590

Mellinger, J., Schalk, G., Braun, C., Preissl, H., Rosenstiel, W., Birbaumer, N., & Kübler, A. (2007). An MEG-based brain-computer interface (BCI). *NeuroImage*, *36*, 581–593. https://doi.org/10.1016/j.neuroimage.2007.03.019

Michielli, N., Acharya, U. R., & Molinari, F. (2019). Cascaded LSTM recurrent neural network for automated sleep stage classification using single-channel EEG signals. *Computers in Biology and Medicine*, *106*. https://doi.org/10.1016/j.compbiomed.2019.01.013

Minguillon, J., Lopez-Gordo, M. A., & Pelayo, F. (2017, January 1). Trends in EEG-BCI for daily-life: Requirements for artifact removal. *Biomedical Signal Processing and Control*, Vol. 31, pp. 407–418. Elsevier Ltd. https://doi.org/10.1016/j.bspc.2016.09.005

Mousa, F. A., El-Khoribi, R. A., & Shoman, M. E. (2016). A Novel Brain Computer Interface Based on Principle Component Analysis. *Procedia Computer Science*, *82*, 49–56. Elsevier B.V. https://doi.org/10.1016/j.procs.2016.04.008

Murugappan, M., & Murugappan, S. (2013). Human Emotion Recognition Through Short Time Electroencephalogram (EEG) Signals Using Fast Fourier Transform (FFT). *2013 IEEE 9th International Colloquium on Signal Processing and Its Applications*, (JUNE 2013), 289–294.

Musallam, Y. K., AlFassam, N. I., Muhammad, G., Amin, S. U., Alsulaiman, M., Abdul, W., … Algabri, M. (2021). Electroencephalography-based motor imagery classification using temporal convolutional network fusion. *Biomedical Signal Processing and Control*, *69*. https://doi.org/10.1016/j.bspc.2021.102826

Nguyen, T., & Pernkopf, F. (2018, March). *Acoustic Scene Classification Using Deep Mixtures Of Parallel Convolutional Neural Networks*.

Olivas-Padilla, B. E., & Chacon-Murguia, M. I. (2019). Classification of multiple motor imagery using deep convolutional neural networks and spatial filters. *Applied Soft Computing Journal*, *75*, 461–472. https://doi.org/10.1016/j.asoc.2018.11.031

Oostenveld, R., & Praamstra, P. (2001). The five percent electrode system for highresolution EEG and ERP measurements. *Clinical Neurophysiology*, *112*(4), 713– 719.

O'shea, K., & Nash, R. (n.d.). *An Introduction to Convolutional Neural Networks*.

Park, C., Took, C. C., & Mandic, D. P. (2014). Augmented complex common spatial patterns for classification of noncircular EEG from motor imagery tasks. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *22*(1), 1–10.

Pesce, E., Ypsilantis, P.-P., Withey, S., Bakewell, R., Goh, V., & Montana, G. (2017). *Learning to detect chest radiographs containing lung nodules using visual attention networks*. https://doi.org/10.1016/j.media.2018.12.007

Peterson, V., Galván, C., Hernández, H., & Spies, R. (2020). A feasibility study of a complete low-cost consumer-grade brain-computer interface system. *Heliyon*, *6*(3). https://doi.org/10.1016/j.heliyon.2020.e03425

Power, S. D., Kushki, A., & Chau, T. (2011). Towards a system-paced near-infrared spectroscopy braincomputer interface: differentiating prefrontal activity due to mental arithmetic and mental singing from the no-control state. *Journal of Neural Engineering*, *8*(6), 66004. https://doi.org/10.1088/1741-2560/8/6/066004

Ramoser, H., Müller-Gerking, J., & Pfurtscheller, G. (2000). Optimal spatial filtering of single trial EEG during imagined hand movement. *IEEE Transactions on Rehabilitation Engineering*, *8*(4), 441–446. https://doi.org/10.1109/86.895946

Rao, R., & Scherer, R. (2010). Brain-Computer Interfacing. In *IEEE Signal Processing Magazine* (Vol. 27).

Rashid, M., Islam, M., Sulaiman, N., Bari, B., Saha, R., & Hasan, M. J. (2020). Electrocorticography based motor imagery movements classification using long short-term memory (LSTM) based on deep learning approach. *SN Applied Sciences*, *2*. https://doi.org/10.1007/s42452-020-2023-x

Saha, S., Mamun, K. A., Ahmed, K., Mostafa, R., Naik, G. R., Khandoker, A., … Baumert, M. (2017). *Progress in Brain Computer Interfaces: Challenges and Trends*.

Salmelin, R., Hámáaláinen, M., Kajola, M., & Hari, R. (1995). Functional Segregation of Movement-Related Rhythmic Activity in the Human Brain. *NeuroImage*, *2*, 237–243.

Samek, W., Kawanabe, M., & Muller, K. R. (2014). Divergence-based framework for common spatial patterns algorithms. *IEEE Reviews in Biomedical Engineering*, *7*, 50–72.

Samek, W., Muller, K. R., Kawanabe, M., & Vidaurre, C. (2012). Brain-computer interfacing in discriminative and stationary subspaces. *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 2873–2876. https://doi.org/10.1109/EMBC.2012.6346563

Samek, W., Vidaurre, C., Müller, K.-R., & Kawanabe, M. (2012). Stationary common spatial patterns for brain-computer interfacing. *Journal of Neural Engineering*, *9*(2), 26013.

Sannelli, C., Vidaurre, C., Muller, K. R., & Blankertz, B. (2012). Common spatial pattern patches: Online evaluation on BCI-naive users. *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 4744–4747. https://doi.org/10.1109/EMBC.2012.6347027

Schirrmeister, R. T., Springenberg, J. T., Fiederer, L. D. J., Glasstetter, M., Eggensperger, K., Tangermann, M., … Ball, T. (2017). Deep learning with convolutional neural networks for EEG decoding and visualization. *Human Brain Mapping*, *38*(11), 5391–5420. https://doi.org/10.1002/hbm.23730

Schlemper, J., Oktay, O., Chen, L., Matthew, J., Knight, C., Kainz, B., … Rueckert, D. (2018). *Attention-Gated Networks for Improving Ultrasound Scan Plane Detection*. Retrieved from http://arxiv.org/abs/1804.05338

Schlemper, J., Oktay, O., Schaap, M., Heinrich, M., Kainz, B., Glocker, B., & Rueckert, D. (2018). *Attention Gated Networks: Learning to Leverage Salient Regions in Medical Images*. Retrieved from http://arxiv.org/abs/1808.08114

Shamshirband, S., Fathi, M., Dehzangi, A., Chronopoulos, A. T., & Alinejad-Rokny, H. (2021, January 1). A review on deep learning approaches in healthcare systems: Taxonomies, challenges, and open issues. *Journal of Biomedical Informatics*, Vol. 113. Academic Press Inc. https://doi.org/10.1016/j.jbi.2020.103627

Simonyan, K., & Zisserman, A. (2014). Very Deep Convolutional Networks for Large-Scale Image Recognition. *ArXiv 1409.1556*.

Sinclair, C., Gasper, M., & Blum, A. (2007). Basic Electronics in Clinical Neurophysiology. In *The Clinical Neurophysiology Primer* (pp. 3–18). https://doi.org/10.1007/978-1-59745-271-7_1

Sitaula, C., & Hossain, M. B. (2021). Attention-based VGG-16 model for COVID-19 chest X-ray image classification. *Applied Intelligence*, *51*(5), 2850–2863. https://doi.org/10.1007/s10489-020-02055-x

Sitges, C., Bornas, X., Llabrés, J., Noguera, M., & Montoya, P. (2010). Linear and nonlinear analyses of EEG dynamics during non-painful somatosensory processing in chronic pain patients. *International Journal of Psychophysiology*, *77*(2), 176–183.

Siuly, S., & Li, Y. (2015). Designing a robust feature extraction method based on optimum allocation and principal component analysis for epileptic EEG signal classification. *Computer Methods and Programs in Biomedicine*, *119*(1), 29–42.

Song, X., Yoon, S. C., & Perera, V. (2013). Adaptive Common Spatial Pattern for single-trial EEG classification in multisubject BCI. In *International IEEE/EMBS Conference on Neural Engineering, NER* (pp. 411–414).

Stewart, A. X., Nuthmann, A., & Sanguinetti, G. (2014). Single-trial classification of EEG in a visual object task using ICA and machine learning. *Journal of Neuroscience Methods*, *228*, 1–14.

Sun, G., Hu, J., & Wu, G. (2010). A novel frequency band selection method for Common Spatial Pattern in Motor Imagery based Brain Computer Interface. *The 2010 International Joint Conference on Neural Networks (IJCNN)*, 1–6.

Taga, G., Homae, F., & Watanabe, H. (2007). Effects of source-detector distance of near infrared spectroscopy on the measurement of cortical hemodynamic response in infants. *NeuroImage*, *38*, 452–460. https://doi.org/10.1016/j.neuroimage.2007.07.050

Tangermann, M., Müller, K.-R., Aertsen, A., N, B., Braun, C., C, B., … Blankertz, B. (2012). Review of the BCI competition IV. *Frontiers in Neuroscience*, *55*.

Teplan, M. (2002). Fundamental of EEG Measurement. *MEASUREMENT SCIENCE REVIEW*, *2*.

Thenmozhi, T., & Helen, R. (2022). Feature Selection Using Extreme Gradient Boosting Bayesian Optimization to upgrade the Classification Performance of Motor Imagery signals for BCI. *Journal of Neuroscience Methods*, *366*. https://doi.org/10.1016/j.jneumeth.2021.109425

Thomas, K. P., Guan, C., Lau, C. T., Vinod, a P., & Ang, K. K. (2009). A new discriminative common spatial pattern method for motor imagery brain-computer interfaces. *IEEE Transactions on Bio-Medical Engineering*, *56*(11 Pt 2), 2730– 2733.

Tiwari, A., & Chaturvedi, A. (2022). Automatic channel selection using multiobjective X-shaped binary butterfly algorithm for motor imagery classification. *Expert Systems with Applications*, *206*. https://doi.org/10.1016/j.eswa.2022.117757

Treacher, A. H., Garg, P., Davenport, E., Godwin, R., Proskovec, A., Bezerra, L. G., … Montillo, A. A. (2021). MEGnet: Automatic ICA-based artifact removal for MEG using spatiotemporal convolutional neural networks. *NeuroImage*, *241*, 118402. https://doi.org/https://doi.org/10.1016/j.neuroimage.2021.118402

Tuncer, E., & Doğru Bolat, E. (2022). Classification of epileptic seizures from electroencephalogram (EEG) data using bidirectional short-term memory (Bi-LSTM) network architecture. *Biomedical Signal Processing and Control*, *73*. https://doi.org/10.1016/j.bspc.2021.103462

Usakli, A. (2010). Improvement of EEG Signal Acquisition: An Electrical Aspect for State of the Art of Front End. *Computational Intelligence and Neuroscience*, *2010*, 630649. https://doi.org/10.1155/2010/630649

van Erp, J., Lotte, F., & Tangermann, M. (2012). Brain-Computer Interfaces: Beyond Medical Applications. *Computer*, *45*(4), 26–34.

Von Bünau, P., Meinecke, F. C., Scholler, S., & Müller, K. R. (2010). Finding Stationary brain sources in EEG data. *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC'10*, 2810–2813. https://doi.org/10.1109/IEMBS.2010.5626537

Waldert, S., Pistohl, T., Braun, C., Ball, T., Aertsen, A., & Mehring, C. (2009). A review on directional information in neural signals for brain-machine interfaces. *Journal of Physiology-Paris*, *103*, 244–254.

Wang, H., Tang, Q., & Zheng, W. (2012). L1-norm-based common spatial patterns. *IEEE Transactions on Biomedical Engineering*, *59*(3), 653–662.

Wang, R., Wang, J., Yu, H., Wei, X., Yang, C., & Deng, B. (2015). Power spectral density and coherence analysis of Alzheimer's EEG. *Cognitive Neurodynamics*, *9*(3), 291–304.

Wang, W., Sudre, G. P., Xu, Y., Kass, R. E., Collinger, J. L., Degenhart, A. D., … Weber, D. J. (2010). Decoding and cortical source localization for intended movement direction with MEG. *Journal of Neurophysiology*, *104*(5), 2451–2461. https://doi.org/10.1152/jn.00239.2010

Wang, Y., Gao, S., & Gao, X. (2005). Common Spatial Pattern Method for Channel Selelction in Motor Imagery Based Brain-computer Interface. *2005 IEEE Engineering in Medicine and Biology 27th Annual Conference*, 5392–5395. https://doi.org/10.1109/IEMBS.2005.1615701

Ward, B., & Mazaheri, Y. (2008). Information transfer rate in fMRI experiments measured using mutual information theory. *Journal of Neuroscience Methods*, *167*, 22–30. https://doi.org/10.1016/j.jneumeth.2007.06.027

Weiskopf, N., Mathiak, K., Bock, S., Scharnowski, F., Veit, R., Grodd, W., … Birbaumer, N. (2004). Principles of a Brain-Computer Interface (BCI) Based on Real-Time Functional Magnetic Resonance Imaging (fMRI). *IEEE Transactions on Bio-Medical Engineering*, *51*, 966–970. https://doi.org/10.1109/TBME.2004.827063

Xu, G., Shen, X., Chen, S., Zong, Y., Zhang, C., Yue, H., … Che, W. (2019). A Deep Transfer Convolutional Neural Network Framework for EEG Signal Classification. *IEEE Access*, *7*, 112767–112776. https://doi.org/10.1109/ACCESS.2019.2930958

Xu, K., Ba, J., Kiros, R., Cho, K., Courville, A., Salakhutdinov, R., … Bengio, Y. (2015). *Show, Attend and Tell: Neural Image Caption Generation with Visual Attention*. Retrieved from http://arxiv.org/abs/1502.03044

Yamashita, R., Nishio, M., Do, R. K. G., & Togashi, K. (2018, August 1). Convolutional neural networks: an overview and application in radiology. *Insights into Imaging*, Vol. 9, pp. 611–629. Springer Verlag. https://doi.org/10.1007/s13244-018-0639-9

Yang, X. (2020). An Overview of the Attention Mechanisms in Computer Vision. *Journal of Physics: Conference Series*, *1693*(1). IOP Publishing Ltd. https://doi.org/10.1088/1742-6596/1693/1/012173

Yong, X., Ward, R. K., & Birch, G. E. (2008a). Robust Common Spatial Patterns for EEG signal preprocessing. *Conference Proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Conference*, *2008*, 2087–2090.

Yong, X., Ward, R. K., & Birch, G. E. (2008b). Sparse spatial filter optimization for EEG channel reduction in brain-computer interface. In *ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings* (pp. 417–420).

Yoo, P. E., John, S. E., Farquharson, S., Cleary, J. O., Wong, Y. T., Ng, A., … Moffat, B. A. (2018). 7T-fMRI: Faster temporal resolution yields optimal BOLD sensitivity for functional network imaging specifically at high spatial resolution. *NeuroImage*, *164*, 214–229. https://doi.org/10.1016/j.neuroimage.2017.03.002

Zhang, J., Wei, Z., Zou, J., & Fu, H. (2020). Automatic epileptic EEG classification based on differential entropy and attention model. *Engineering Applications of Artificial Intelligence*, *96*. https://doi.org/10.1016/j.engappai.2020.103975

Zhang, Y., Jin, J., Wang, X., & Wang, Y. (2016). Motor imagery EEG classification via Bayesian extreme learning machine. In *International Conference on Information Science and Technology (ICIST)* (pp. 27–30).

LIST OF PUBLICATIONS

Che Man, M. A., Shapiai, M. I., Ramli, A.K., & Elias, K.A. (2022). EEG to Brain Topography Classification using Convolutional Neural Networks. In *Asian Scholars Network International Conference* (pp. 1–14).