COMPACT AND INTERPRETABLE CONVOLUTIONAL NEURAL NETWORK ARCHITECTURE FOR ELECTROENCEPHALOGRAM BASED MOTOR IMAGERY DECODING

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DEDICATION

This thesis is dedicated to my father, Ahmad Izzuddin Bin Osman Salleh who has always encouraged me to pursue my PhD studies. He has always been my source of inspiration and motivation in acquiring knowledge since my childhood years. The quote "knowledge is power" was first told to me by him, and it has always been one of my life principles.

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ABSTRACT

Recently, due to the popularity of deep learning, the applicability of deep Neural Networks (DNN) algorithms such as the convolutional neural networks (CNN) has been explored in decoding electroencephalogram (EEG) for Brain-Computer Interface (BCI) applications. This allows decoding of the EEG signals end-to-end, eliminating the tedious process of manually tuning each process in the decoding pipeline. However, the current DNN architectures, consisting of multiple hidden layers and numerous parameters, are not developed for EEG decoding and classification tasks, making them underperform when decoding EEG signals. Apart from this, a DNN is typically treated as a black box and interpreting what the network learns in solving the classification task is difficult, hindering from performing neurophysiological validation of the network. This thesis proposes an improved and compact CNN architecture for motor imagery decoding based on the adaptation of SincNet, which was initially developed for speaker recognition task from the raw audio input. Such adaptation allows for a very compact end-to-end neural network with state-of-the-art (SOTA) performances and enables network interpretability for neurophysiological validation in terms of cortical rhythms and spatial analysis. In order to validate the performance of proposed algorithms, two datasets were used; the first is the publicly available BCI Competition IV dataset 2a, which is often used as a benchmark in validating motor imagery (MI) classification algorithms, and a primary data that was initially collected to study the difference between motor imagery and mental rotation task associated motor imagery (MI+MR) BCI. The latter was also used in this study to test the plausibility of the proposed algorithm in highlighting the differences in cortical rhythms. In both datasets, the proposed Sinc adapted CNN algorithms show competitive decoding performance in comparisons with SOTA CNN models, where up to 87% decoding accuracy was achieved in BCI Competition IV dataset 2a and up to 91% decoding accuracy when using the primary MI+MR data. Such decoding performance was achieved with the lowest number of trainable parameters (26.5% - 34.1% reduction in the number of parameters compared to its non-Sinc counterpart). In addition, it was shown that the proposed architecture performs a cleaner band-pass, highlighting the necessary frequency bands that focus on important cortical rhythms during task execution, thus allowing for the development of the proposed Spatial Filter Visualization algorithm. Such characteristic was crucial for the neurophysiological interpretation of the learned spatial features and was not previously established with the benchmarked SOTA methods.

ABSTRAK

Baru-baru ini, disebabkan populariti pembelajaran mendalam, kebolehgunaan algoritma Rangkaian Neural Dalam (DNN) seperti rangkaian neural konvolusi (CNN) telah diterokai dalam penyahkodan electroencephalogram (EEG) untuk aplikasi Antaramuka Komputer-Otak (BCI). Ini membolehkan penyahkodan isyarat EEG dari hujung ke hujung, dan menghapuskan proses renyah dalam penalaan secara manual setiap proses dalam saluran paip penyahkodan. Walau bagaimanapun, senibina DNN semasa yang terdiri daripada berbilang lapisan tersembunyi dan jumlah parameter yang banyak, tidak dibangunkan untuk tugas penyahkodan dan pengelasan EEG, menjadikannya kurang berprestasi untuk tujuan penyahkodan isyarat EEG. Selain itu, DNN biasanya dianggap sebagai kotak hitam dan penafsiran terhadap apa yang dipelajari oleh rangkaian tersebut dalam menyelesaikan tugas pengelasan adalah sukar, sekaligus menghalang daripada melaksanakan pengesahan neurofisiologi rangkaian. Tesis ini mencadangkan seni bina CNN yang lebih baik dan padat untuk penyahkodan imej motor berdasarkan penyesuaian SincNet, yang pada mulanya dibangunkan untuk tugas pengecaman suara daripada input audio mentah. Penyesuaian sedemikian membolehkan rangkaian neural dari hujung ke hujung yang sangat padat dengan prestasi terkini (SOTA) dan membolehkan kebolehtafsiran rangkaian untuk pengesahan neurofisiologi dari segi irama kortikal dan analisis spatial. Untuk mengesahkan prestasi algoritma yang dicadangkan, dua set data telah digunakan; yang pertama ialah set data BCI Competition IV 2a yang tersedia secara umum, yang sering digunakan sebagai penanda aras dalam mengesahkan algoritma pengelasan imejan motor (MI), dan data utama yang pada mulanya dikumpulkan untuk mengkaji perbezaan antara imejan motor dan tugas putaran mental berkaitan motor imejan (MI+MR) BCI. Yang terakhir ini juga digunakan dalam kajian ini untuk menguji kebolehpercayaan algoritma yang dicadangkan dalam menyerlahkan perbezaan dalam irama kortikal. Dalam kedua-dua set data, algoritma CNN yang disesuaikan daripada Sinc yang dicadangkan menunjukkan prestasi penyahkodan kompetitif berbanding model SOTA CNN, di mana ketepatan penyahkodan sehingga 87% dicapai dalam dataset BCI Competition IV 2a dan sehingga 91% ketepatan penyahkodan apabila menggunakan data utama MI+MR. Prestasi penyahkodan sedemikian dicapai dengan bilangan parameter boleh dilatih yang terendah (26.5% - 34.1% pengurangan dalam bilangan parameter berbanding padanannya yang bukan Sinc). Di samping itu, telah ditunjukkan bahawa seni bina yang dicadangkan melakukan penapisan jalur yang lebih bersih, menonjolkan jalur frekuensi yang diperlukan yang menumpukan pada irama kortikal yang penting semasa pelaksanaan tugas, sekali gus membolehkan pembangunan algoritma Visualisasi Penapis Spatial yang dicadangkan. Ciri sedemikian adalah penting untuk tafsiran neurofisiologi ciri spatial yang dipelajari dan tidak pernah dibangunkan dengan kaedah SOTA yang ditanda aras.

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LIST OF ABBREVIATIONS

ANN	-	Artificial Neural Network
AI		Artificial Intelligence
ALS	-	Amyotrophic Lateral Sclerosis
BCI	-	Brain Computer Interface
BN		Batch Normalization
CART		Classification and Regression Tree Algorithm
CFC		Cross Frequency Coupling
CNN	-	Convolutional Neural Network
CSP		Common Spatial Pattern
DSP	-	Digital Signal Processing
ECoG	-	Electrocorticography
EEG	-	Electroencephalogram
ERD		Event Related De-Synchronisation
ERN		Error Related Negativity Response
ERP		Event Response Potential
ERS		Even Related Synchronisation
ELU		Exponential Linear Unit
FBCSP		Filter Bank Common Spatial Pattern
fMRI	-	Functional Magnetic Resonance Imaging
FPR		False Positive Rate
GFT		Graph Fourier Transform
GSP		Graph Signal Processing
IIR		Infinite Impulse Response
KNN		K-th Nearest Neighbour
LDA		Linear Discriminant Analysis
LSTM		Long Short Term Memory
MI		Motor Imagery
MI+MR		Mental Rotation associated Motor Imagery
MIBIF		Mutual Independent best individual filter
MRCP		Motor Related Cortical Potential

RDTM		Riemannian Distance To Mean
RELU		Rectified Linear Unit
RNN		Recurrent Neural Network
RMS		Root Mean Square
ROC		Receiver Operating Characteristic
SMR		Sensory Motor Rythms
SOTA	-	State of The Art
SSVEP	-	Steady-State Visually Evoked Potential
TPR		True Positive Rate

LIST OF SYMBOLS

A_{train}	Average training accuracy
$A_{validation}$	Average validation accuracy
$\boldsymbol{\beta}$	Shift parameter
C	Number of EEG Channels
D	Diagonal matrix that contains eigenvalues
E	Single trial EEG recordings
E	Network's validation loss
F	Total number of bandpass to be used with CNN
F_K	Number of temporal convolutional filter
F_s	Number of spatial filters
F_p	Number of pointwise convolution filters
f_1	Low cut-off frequency
f_2	High cut-off frequency
f_1^{abs}	Absolute value of the low cut-off frequency
f_{band}	Filter's band size
γ	Minibatch scale parameter
h	Hop-size (sliding window parameter)
$h[n]$	Kernel of length L
i_{max}	Convolution filter index that gives out maximum RMS
j_{max}	Temporal filter index that gives out maximum RMS
K	Temporal kernel size
κ	Kappa-Cohen coefficient
l_{FK}	Number of temporal adaptive kernel
L	Number of the all possible output labels of a CNN
$\mathcal{L}$	Loss function of a CNN
N_i	Recorded trial for subject-i
n	Discrete n-th sample
p	Dropout rate
$\sum_{b1}$	Estimated co-variance of the first band-pass

$\sum_{b2}$	Estimated co-variance of the second band-pass
$\hat{\boldsymbol{\sigma}}_{\boldsymbol{B}}$	Minibatch *B* standard deviation
$\boldsymbol{o_j}$	Output of *j-th* neuron
P	Patience threshold(early stopping)
p_o	Classification accuracy (Kappa statistics)
p_e	The proportion of times classes are expected to agree by chance (Kappa statistics)
$\%OV$	Percent overshoot
R_{ELU}	Exponential Linear Unit activation function
R_{ReLU}	Rectified Linear Unit activation function
$RMS_{i,j}$	RMS value of *i*-th temporal filter and *j-th* spatial filter
T	EEG trial's length
T'	Windows's size (sliding window approach)
T_{sc}	Temporal convolution kernel's size
θ	Network parameters
$\hat{\boldsymbol{\mu}}_{\boldsymbol{B}}$	Minibatch's sample mean
$w[n]$	Hamming's window function
$\boldsymbol{w}$	Neural network's weights
W_c	Spatial filter weights
$\mathbf{W}$	CSP projection matrix
$x[n]$	Input signal
$\boldsymbol{x}$	Batch normalization input
X^j	*j-th* original trial
$y[n]$	Filtered output from discrete convolution process
$\mathbf{Z}$	Spatially filtered signal

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CHAPTER 1

INTRODUCTION

1.1 Research Background

A brain-computer interface (BCI) can be defined as a system that translates brain activity patterns into messages or commands that represent the user's intention or condition by using the direct brain to computer mode of communication [1]–[3]. Until recently, the dream of being able to control one's environment by using thoughts alone is considered science fiction. Advancements in technology have allowed for a thorough understanding of the brain, enabling the developments of machines capable of decoding and interpreting the complex nature of the brain process. Among the earliest form of BCI system was demonstrated by professor Jacques Vidal in which the feasibility of controlling a cursor-like graphical object on a screen was shown by detecting certain features in the brain's electrical signals or electroencephalography (EEG) [4] through the use of electrodes placed on subject's scalp.

Since then, many studies have successfully demonstrated the feasibility of various BCI system applications with a wide range of system complexity. Apart from using the non-invasive EEG, researchers have explored the use of the latest medical technology ranging from the complex functional magnetic resonance imaging (fMRI) [5], [6] to the more invasive electrocorticography (ECoG) [7] and microarrays electrode [8] for this purposes. One of the most apparent and noble reasons for the use of this technology is that it brings hope to "locked-in" individuals, who are cognitively intact but without useful muscle functions and those who are suffering from the most severe motor disabilities, including people with amyotrophic lateral sclerosis (ALS), spinal cord injury, stroke, and other neuromuscular diseases or injuries [9]. When the brain's ability to move muscles or navigate one's environment is lost, this technology allows us to directly read the brain waves pattern and translate users' mental intention. For this reason, various medical applications using BCI have been explored including restoring communications for locked-in patients [10], [11], restoration of motor control via neuroprosthesis and robotics limb [12], restoration of independent locomotion through the use of motorized wheelchair [13], [14], BCI based environmental control [15], [16], and neurorehabilitation [17], [18]. Figure 1.1 illustrates the typical BCI process and its applications. Apart from its obvious medical uses, BCI has recently been commercialized as an off-the-shelf device to increase focus and assist in meditation. As an example, the single-channel EEG headset, Mindwave Mobile from Neurosky is marketed as an affordable BCI tool to improve attention and meditation [19], [20].

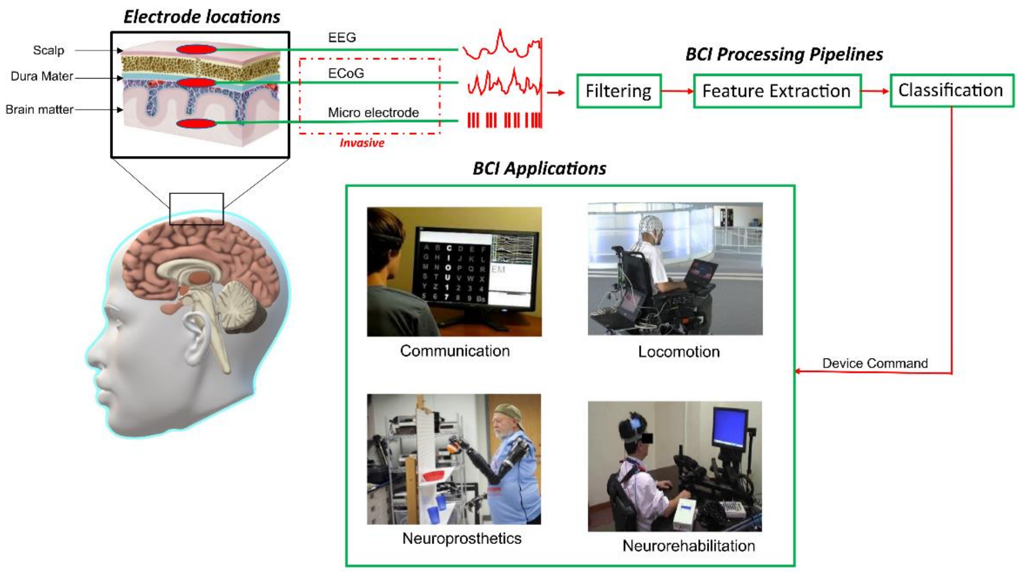

Figure 1.1 BCI processing pipelines and its applications

In most BCI systems, the derivation of meaningful information from the raw brain's bioelectrical signals typically follows a similar pipeline. From the non-invasive EEG to the surgically required ECoG and micro-electrode arrays, extraction of these bioelectrical signals will usually be followed by filtering, feature extraction, and signals classification. In the filtering stage, noise from the signals will be removed through suitable digital signal processing (DSP) algorithms. The use of bandpass and notch filters in DSP, for example, helps the system to focus on the most relevant neurophysiological rhythms that contain useful information. This process is then followed by a feature extraction stage in which essential features from the signals are extracted via statistical analysis or automated using computer algorithms. These features are finally classified in the final stage of the pipeline using more general machine learning algorithms.

Although there exist multiple brain-to-computer communication methods, for practicality, the use of EEG signal is considered more popular due to its relatively low-cost requirement and non-invasive nature. EEG method of acquiring brain electrical signal works by measuring the electrical potentials from electrodes placed on the human scalp. Since its discovery in 1929 by German psychiatrist Hans Berger, EEG's use for BCI has gained considerable interest as it allows practical acquisition of brain signals to be applied in a real-life environment. Deriving meaningful signals from EEG follows the mentioned BCI processing pipeline, and generally, for BCI applications, such signals are processed to detect either the user's Evoked Potentials (EP) or the Event-Related Synchronous/De-Synchronous signals (ERD/ERS) [1]. In the case of ERD/ERS, this includes Imagery signals such as the Motor Imagery (MI) signals (signals produced during imagined or overt movement of human limbs) or Mental Imagery signals (signals produced while performing mental tasks such as mental rotation, mental arithmetic, mental-spatial visualization etc.) [21]. Detecting such imagery signals open up many interesting BCI applications.

While very promising for many applications, EEG-based BCI, especially BCI that relies on MI detection, is still scarcely available outside of laboratories [9]. The lack of availability is mainly due to their low reliability, as they often gave erroneous mental commands from the user, and most EEG-based apparatus are impractical to be used outside of the laboratory. One of the main challenges for researchers in the BCI community is improving a BCI system's reliability and practicality [22]. Therefore, to achieve this, improvement towards the BCI system's two main elements are needed to be considered: 1: improvement towards the computer side of the system, in terms of computational performance and classification algorithm. 2: Improvement towards the user side of the system by enhancing user's ability in controlling a BCI system.

1.2 Problem Statement

In addressing improvement towards the computer side of a BCI system, much research has focused on improving computational algorithm performance in terms of classification accuracy, reliability, and practicality. These include algorithms for filtering the raw EEG signal, extracting relevant features, and finally classifying those features into relevant classes [23]. Recently, due to the computer technology advancement and popularity of deep learning and artificial intelligence (AI), algorithms such as the Convolutional Neural Network (CNN) have been considered state-of-the-art (SOTA) in image classification, speech recognition, language processing, and other domains that requires the use of signal classification or machine learning.

Such popularity has led many researchers to explore the applicability of CNN towards decoding EEG for BCI purposes [24]–[26]. One main advantage of using a deep CNN algorithm is that it enables end-to-end learning and decoding directly from the raw EEG signals to perform the classification task in the context of BCI. This allows bypassing the traditional filtering and feature extraction stage in the conventional BCI processing pipeline. Such features prove attractive to researchers as the traditional processes in a BCI pipeline are time-consuming and cumbersome for real life applications. Deep learning algorithms allow for a faster development time as manually tuning each stage in the processing pipeline is now replaced by artificial neural networks (ANN), in which parameter tuning is handled automatically via network optimization [27].

However, deep learning algorithms are generally computationally expensive and require a huge amount of data for the neural network (NN) training and execution (inference) [28]–[30]. Such issues make implementing deep CNN for EEG decoding difficult as the amount of data available in general EEG experiments is limited. Apart from this, using standard "deep" CNN (denotes that the CNN contains many hidden layers) architectures for EEG decoding where the number of data is limited causes the network to overfit; an issue where the network optimizes too well on the training data, but fails to generalize on a new set of data. Hence, in this case, a more compact and shallower NN architecture is often desirable [24], [25], as it eliminates the network overfitting issue and generalizes well on new data, which is crucial for real implementation. Another advantage of having a compact CNN architecture is that it allows for a CNN with fewer parameters, reducing computational requirement in training and deploying the trained CNN.

Another drawback of using end-to-end CNN is that although it can result in SOTA performance for decoding accuracy, it is hard to interpret for analysis purposes. Such interpretability issue makes CNN or any NN-based architecture in general difficult to identify the features that the network learned and extracted to solve the classification task [31]. In the context of BCI research, such a drawback resulted in difficulty in performing neurophysiological validation as to why the CNN is able to learn from the raw EEG data and what features are being extracted. For example, in an EEG-based BCI system, it is important to identify the spectral and spatial features to validate which cortical rhythm (frequency band) and which cortical areas contribute to deriving meaningful information from EEG data. Hence, developing an interpretable CNN architecture is crucial for performing such an analysis.

The second element in a BCI system that needs to be addressed is improving the system's usability or the user’s ability to control or use the system itself. In this case, little research has been done toward achieving this goal. A BCI system is analogous to a car race competition in which the user is the car driver, while the computer side is the car itself. Race performance depends on the driver’s ability to control the car and engine performance and handling. One way to enhance user-side performance and adaptability to the BCI system is by introducing a suitable training protocol before actual user engagement. For example, this can be achieved by introducing a training protocol that addresses the user’s ability to perform kinaesthetic MI for an MI-based BCI system [32], [33]. This study hypothesizes a novel method that associates mental imagery tasks with motor imagery to improve the user’s kinaesthetic imagery. This improvement is because such association is theorized to allow for concrete discrimination of EEG signals, hence allowing the BCI system to discrimate better between EEG signals during certain motor task execution, resulting in better classification performance. Such improvement is also essential in addressing the inter-and intra- variability of decoding accuracy between BCI's users [34].

1.3 Research Objectives

Based on the scenario aforementioned, it is imperative to develop a good computer algorithm and ensure that BCI users undergo a suitable training protocol for actual EEG-based BCI deployment. In achieving this aim, the objectives of this research project are as follows:

i. To develop new CNN architecture for MI-based BCI decoding that is compact and interpretable for analysis.

ii. To validate the plausibility of developed CNN architecture in terms of its decoding performance and neurophysiological validity.

iii. To improve users' usability of a BCI system by introducing novel mental to motor association tasks into MI-based BCI training protocol as well as for validation of developed CNN architecture.

1.4 Research Scopes

The research scopes of this study are listed as follows:

i. The research focuses on Motor Imagery (MI) as the BCI paradigm.

ii. EEG signals recoding as a means to represent the brain's electrical activity.

iii. Validation of proposed CNN architecture using both primary and secondary datasets.

iv. The secondary data consists of the publicly available dataset, BCI Competition IV dataset 2a (available at http://bnci-horizon-2020.eu/database/data-sets), often used as the de facto standard in gauging the performance of MI-based BCI classification algorithm. This dataset consists of EEG recordings taken from 9 participants using 19 channels electrodes.

v. Primary data consist of EEG samples collected from 13 participants, mainly students from Universiti Teknologi Malaysia (UTM), who had informed consent prior to data collection. Before data collection, ethical approval was obtained from National Medical Research Register (NMRR) (research registry number: **NMRR-19-1671-47228**).

vi. All EEG recordings are recorded using NVX-52 EEG amplifier from Medical Computer System (MKS) in which only 22 EEG channels were utilized following the international 10-20 standard.

vii. Decoding of the EEG-based MI signals into left and right-hand movement intentions for primary data.

viii. Use of the open-source python and its packages for algorithm construction and analysis: Tensorflow-Keras, Scikit-learn for algorithm development and Python MNE for EEG related analysis.

1.5 Research Contributions

By achieving the previously mentioned objectives, this research study provides several contributions towards the field of BCI, specifically towards the use of recent deep learning methodologies in decoding EEG based motor MI signals. Concretely, the contributions are listed as follows:

(a) **Compact CNN architecture for EEG based MI decoding** A new compact and shallow CNN architecture for MI decoding has been developed using the industry's standard deep learning framework (Google's Tensorflow and Keras). The developed architecture performs comparably with the benchmarked SOTA CNN architecture, albeit with the least trainable network parameters. Such compactness made the architecture attractive to be deployed on resources constrained embedded computers. Furthermore, all codes are made open-source and are published on our Github. (https://github.com/TarmiziIzzuddin/Sinc_CNN_EEG_decode)

(b) **Interpretable CNN architecture for neurophysiological validation.** Apart from being compact, the developed architecture is also engineered to be interpretable. Such features made it possible for users to "peer" in the network in order to perform neurophysiological validation and analysis. More concretely, using algorithms outlined in chapter 3, it is now possible to identify the necessary cortical rhythms and areas that the network focuses on to solve the decoding task. Similarly, this algorithm was also made available on our GitHub.

(c) **New BCI training protocol that enables user's kinaesthetic MI** As this research also addresses the user's side of the BCI system, chapter 3 in this thesis has outlined the proposed BCI training protocol that enhances the user's kinaesthetic ability in using a BCI system. Such protocol enhances certain cortical activation in the brain, making it more distinguishable for computer algorithms to discriminate between tasks. In addition, data collected using this protocol is the study's primary data and was validated against the developed CNN architecture for neurophysiological validation.

1.6 Thesis Organizations

This thesis is organized into six different chapters that reflect the sequence of the process involved in the development of the proposed CNN architecture for decoding MI signals. A brief outline of the thesis is as follows:

Chapter 1 presents the research background of a BCI system, the research's motivation and its problem statement. In addition, the research objectives are formulated, and the research's scope is presented. Finally, the contribution of the research is listed.

Chapter 2 describes the approaches in achieving an EEG-based BCI system in detail. The numerous BCI paradigms are thoroughly reviewed, and the current deep NN methodologies are discussed. Research gaps are identified based on the review, and the research directions are constructed.

Chapter 3 explains the overall research methodology in achieving all of the research objectives. This includes a description of datasets used to validate the proposed CNN. In addition, details on the research protocol for collecting primary data, the proposed BCI protocol, and the research tools are also described in detail in this chapter. Finally, a thorough methodology for constructing the proposed compact and interpretable CNN architecture based on SincNet is shown here.

Chapter 4 and 5 present the validation of the prosed CNN architecture in decoding EEG based MI signals. In chapter 4, the decoding performance of the proposed architecture is compared and benchmarked with SOTA architectures toward decoding the BCI competition IV dataset 2a (secondary data) while in chapter 5 focuses on performing validation of the proposed network as an analysis tool for interpreting learned neurophysiological features of the primary dataset.

Finally, chapter 6 presents the concluding remarks and recommendations of possible future works that can be taken in order to further test and improve the developed CNN architecture.

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LIST OF PUBLICATIONS

Journals

1. **Izzuddin**, **T**. **A**., Safri, N.M., Othman, M. A.,. (2021) 'Compact convolutional neural network (CNN) based on SincNet for end-to-end motor imagery decoding and analysis', *Biocybernetics and Biomedical Engineering*, 41, 1629–1645 (**ISI-WoS Indexed, Q2, IF: 4.314**)

2. **Izzuddin**, **T**. **A**., Safri, N.M., Othman, M. A.,. (2021) 'Mental imagery classification using one-dimensional convolutional neural network for target selection in single-channel BCI-controlled mobile robot', *Neural Computing and Applications*, 33 (11), 6233–6246 (**ISI-WoS Indexed, Q1, IF: 5.606**)

3. **Izzuddin**, **T**. **A**., Safri, N.M., Othman, M. A.,. (2018) 'Single Channel Electroencephalogram (EEG) Brain Computer Interface (BCI) Feature Extraction and Quantization Method for Support Vector Machine Classification', *International Journal of Engineering & Technology*, 7 (4), 6233–6246 (**SCOPUS Indexed, Q4)**