An Evaluation of Different Fast Fourier Transform - Transfer Learning Pipelines for the Classification of Wink-based EEG Signals

Jothi Letchumy Mahendra Kumar1, Mamunur Rashid2, Rabiu Muazu Musa3, Mohd Azraai Mohd Razman1, Norizam Sulaiman2, Rozila Jaitani4, and Anwar P.P. Abdul Majeed1,5*

1Innovative Manufacturing, Mechatronics and Sports Laboratory, Faculty of Manufacturing and Mechatronics Engineering Technology, Universiti Malaysia Pahang (UMP), 26600 Pekan, Pahang Darul Makmur, Malaysia
2Faculty of Electrical and Electronics Engineering Technology, Universiti Malaysia Pahang, 26600 Pahang, Malaysia.
3Centre for Fundamental and Liberal Education, Universiti Malaysia Terengganu (UMT), 21030 Kuala Nerus, Terengganu Darul Iman, Malaysia
4Faculty of Electrical Engineering, Universiti Teknologi MARA (UiTM), 40450 Shah Alam, Selangor Darul Ehsan, Malaysia
5Centre for Software Development & Integrated Computing, Universiti Malaysia Pahang, Gambang, Malaysia

ABSTRACT – Brain Computer-Interfaces (BCI) offers a means of controlling prostheses for neurological disorder patients, primarily owing to their inability to control such devices due to their inherent physical limitations. More often than not, the control of such devices exploits the use of Electroencephalogram (EEG) signals. Nonetheless, it is worth noting that the extraction of the features is often a laborious undertaking. The use of Transfer Learning (TL) has been demonstrated to be able to mitigate the issue. However, the employment of such a method towards BCI applications, particularly with regards to EEG signals are limited. The present study aims to assess the effectiveness of a number of DenseNet TL models, viz. DenseNet169, DenseNet121 and DenseNet201 in extracting features for the classification of wink-based EEG signals. The extracted features are then classified through an optimised Random Forest (RF) classifier. The raw EEG signals are transformed into a spectrogram image via Fast Fourier Transform (FFT) before it was fed into selected TL models. The dataset was split with a stratified ratio of 60:20:20 into train, test, and validation datasets, respectively. The hyperparameters of the RF model was optimised through the grid search approach that utilises the five-fold cross-validation technique. It was established from the study that amongst the DenseNet pipelines evaluated, the DenseNet169 performed the best with an overall validation and test accuracy of 89%. The findings of the present investigation could facilitate BCI applications, e.g., for a grasping exoskeleton.

Introduction

The Institute for Health Metrics and Evaluation (2017) reported that stroke is the third leading cause of mortality in Malaysia. Whereas, the Global Burden of Disease Report (2016) has predicted that stroke will be the second leading cause of mortality in 2040 [1]. It is worth noting that stroke is also one of the top ten leading reasons for fatality rate and hospitalisation in Malaysia. Owing to the increasing trend of this disease, the World Health Organization (WHO) has announced the need for an active form of rehabilitation initiatives for post-stroke patients [2].

Stroke is one of the most common neurological diseases [3]. The main reason for stroke is the blockage or burst of the blood vessels that carry oxygen to the brain [4]. The interruption of brain signals due to the aforesaid reason could affect the patients’ motor functions, amongst others [5]. It is worth to note that there is a myriad of techniques that have been used to monitor brain signals, namely Electroencephalography (EEG), Electrocorticography (ECoG), functional Magnetic Resonance Imaging (fMRI), Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET) [6]. It is worth noting that EEG is the most common method for capturing brain signals amongst the above-mentioned techniques, primarily due to its excellent temporal resolution, noninvasive, usability, and low set-up costs [7], [8].

EEG is increasingly relevant in the diagnosis and treatment of neurodegenerative diseases [10]. Nevertheless, conventional means of analysing such signals are visually based and hence time-consuming, error-prone, as well as unreliable. Therefore, there is a need to develop an automated EEG classification method to ensure proper evaluation and treatment of such neurological diseases [9]. In the same vein, the
role of innovative technologies such as the Brain-Computer Interface (BCI) that utilises EEG signals is non-trivial towards facilitating rehabilitation efforts [10].

Related Works

To date, various approaches have been employed by researchers in the attempt of classifying EEG signals over the last decade [13–16]. The detection of intentional eye blink through EEG signals was investigated by [11]. Different time-domain features were extracted in the investigation of intentional eye blinking signals. The features that were extracted from the signals obtained were maximum amplitude, minimum amplitude in each sample window and the kurtosis of the present sample, kurtosis of the previous and kurtosis of the nested sample. The samples were divided into two sets of datasets, which are 70% and for training datasets and 30% for testing datasets. The classification of the signals was evaluated with Radial Basis Function (RBF), multilayer perceptron (MLP) with Feed Forward Back Propagation (FFBP), and MLP-Cascade Forward Back Propagation (CFBP). The RBF model was ascertained to be the best with a classification accuracy (CA) of 100%.

Abdelhameed and Bayoumi [12] proposed a multimodal emotion recognition framework by combining facial expression and EEG, based on a valence-arousal emotional model. For facial expression detection, they followed a transfer learning approach for multi-task convolutional neural network (CNN) architectures to detect the state of valence and arousal. For EEG detection, two learning targets (valence and arousal) were detected by different support vector machine (SVM) classifiers, separately. They used two emotion datasets, namely, the Database for Emotion Analysis using Physiological Signals (DEAP) and MAHNOB human-computer interface (MAHNOB-HCI) to evaluate their method. The results suggest that the combination of facial expressions and EEG information for emotion recognition compensates for their defects as single information sources.

A deep learning-based method that automatically exploits the time-frequency spectrum of the EEG signal was investigated in [13]. Through the use of Continuous Wavelet Transform (CWT), the authors extracted the time-frequency spectrogram from the EEG signals taken from ten (10) healthy subjects (ISRUC-Sleep dataset) and converted them to RGB images. The images were classified using a transfer learning method based on the AlexNet pre-trained Convolutional Neural Network (CNN) model. It is worth mentioning at this juncture, that the main advantage of this approach is the elimination for the need of a manual feature extraction and selection technique. It was shown from the study that the proposed technique could yield a CA of 84%.

To the best of the authors’ knowledge, the capability of a hybrid Transfer Learning (TL) – Random Forest (RF) pipeline from spectrogram attained via Fast Fourier Transform (FFT) in classifying the wink-based EEG signals has yet been investigated. Therefore, the objective of this paper is to appraise the ability of different DenseNet TL-based models in extracting features that are then classified by an optimised RF model. It is hypothesised that the proposed technique could distinguish well the different categories of EEG signals attained from the winking expressions. The outcome of this study should be able to improve the patients’ daily lives quality through the implementation of BCI technologies [8], [14], [15].

Methodology

Typically, the classification of EEG signals consists of four steps, namely signal collection, preprocessing, feature extraction and feature selection as well as classification [9], [16], [17]. Nonetheless, this study will embark on the use of TL for feature extraction. The main aim of this study is to classify Right, Left and No winks that use TL models, specifically from the DenseNet family to extract the image-based features and RF Machine Learning (ML) models.

In developing such a system, the EEG Emotiv Insight (EI) Mobile device was used to collect the wink-based EEG signals. This device consists of five (5) channels, including the reference channel [26]. EI has advanced electronics that are fully optimised to produce clean and robust signals [18]. The aforesaid five channels are AF3, AF4, T7, T8, and Pz, respectively. The position of these nodes was determined according to the international standardised 10-20 system.

Five healthy (three males and two females aged between 22 and 29) subjects participated in this study. The subjects have no history of neurological disease or psychiatric disorder as well as having normal vision. None of them has any prior experience in the experiment that will be carried nor aware of Brain-Computer Interface (BCI) applications. The study has been approved by an institutional research ethics committee (FF-2013-327).

The experiment was conducted in a controlled room without any other noise from the environment located at the Faculty of Electrical and Electronics Engineering Technology, Universiti Malaysia Pahang. This is to remove the environmental disruption to be registered along with the emitted EEG signal. The subjects sat on an ergonomic chair. They were told to remain in a relaxed position and to stay relaxed

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without any extra physical activity throughout the experiment. The slide show demonstration was shown as a guide for the participants to perform the experiment appropriately. The distance between the subject and the monitor that displays the slide is one metre.

The experiment paradigm that consists of five left and right wink trials is shown in Figure 1. The first slide shows that the participants are in a 5-second resting position, followed by winking either left or right for the next 5 seconds. Then rest another 5 seconds and replicate the winking action shown on the slide show. The whole data collection for left and right winking carried out for 60 seconds. All the subjects performed the two types of winking action for one minute. In this study, the FFT is used to convert the brain signal from the time domain into the time-frequency domain.

Conversion of EEG Signal: Spectrogram

Spectrogram provides a compromise between time and frequency resolution [19]. It is a visualisation of a signal’s frequency spectrum, as it differs over time. A spectrogram is usually depicted as a heat map, like an image with the intensity shown by varying the colour or brightness. The digitally sampled data is separated into segments that normally overlap, and the FFT measures the frequency spectrum magnitude for each section [20], [21].

The windows obtain a time-slice of the signal, during which the spectral characteristics are nearly constant [22]; the obtained segments shift the time window with some overlapping. The spectrogram is defined as the magnitude of \( S(m,k) \), represented as \( A(m,k) \) as shown in Equation 3:

\[
A(m,k) = \frac{1}{N} |S(m,k)|^2
\]

(1)

Typically, a configuration of a spectrogram is as follows: the x-axis specifies the time, the y-axis serves frequency, and the third dimension is the amplitude of a frequency-time pair coded in color.

Feature Extraction: Transfer Learning (TL)

In the field of bioinformatics, the notion of limited or scarce data is a rather grave concern. Nevertheless, the use of TL could mitigate this predicament [23], [24]. TL is an increasingly popular machine vision approach that allows for the development of accurate models in a computationally inexpensive fashion [25]–[27]. Instead of initiating the learning process or building the convolutional neural network (CNN) models from scratch, TL leverages from pre-trained CNN models that have been trained on reasonably large datasets [28]. In this study, three DenseNet pre-trained CNN models are employed in this research, as listed in Table 1.

| Table 1. List of TL models implemented in this research. |
|----------------------------------------------------------|
| No. | TL Models       | Flatten Size | Input Image Size |
|-----|-----------------|--------------|------------------|
| 1   | DenseNet 121    | 7*7*1024     |                   |
| 2   | DenseNet 169    | 7*7*1664     | 224*224          |
| 3   | DenseNet 201    | 7*7*1920     |                  |

| Table 2. List of hyperparameters values in RF classifier. |
|----------------------------------------------------------|
| No. | Hyperparameters | RF Models             |
|-----|-----------------|------------------------|
| 1   | n_estimator     | 10, 20, 30, 40, 50, 60 & 70 |
| 2   | max_depth       | 10, 20, 30, 40, 50, 60 & 70 |
| 3   | Criterion       | Gini and Entropy       |

Classifier: Random Forest (RF)

Random Forest (RF) is an ensemble learning method that could either be used for classification as well as regression [29]. RF essentially yields its classification based on a collection of decision trees [30]. The number of trees and the depth of the trees are denoted as \( n \)-estimator and \( \max \)-depth, respectively. Both the Gini and Entropy indexes were investigated as the basis of the splitting node. Table 2 tabulates the hyperparameters that were tuned using grid search approach in the present study through the five-fold cross-validation technique [31]–[33].

Performance Evaluation

A stratified 60:20:20 ratio hold-out strategy was used for splitting the training, testing and validation datasets, respectively [34]. In the present study, different performance measures were used to evaluate the developed pipelines, namely classification accuracy (CA), precision, recall, and f1-score, apart from the confusion matrix. The models were developed and evolved on a Python IDE, i.e., Spyder 3.7 with associated Keras and sklearn libraries.

Results and Discussion

The EEG winking data consists of six sets having two single-channel of EEG signals. Each data set was collected at the sampling rate of 128 samples per second of each channel. The datasets were divided into segments to obtain only the winking signals. Thus, each segment is composed of 640 samples. Using the FFT algorithm, the digital signals were converted images with a dimension of \( 224 \times 224 \) as per the input size for the TL models. Figure 2 shows the plot of raw data of five trials of the EEG Right Winking signal of subject A, whilst Figure 3 shows the spectrogram of the converted digital signals.
Figure 1. The experimental paradigm.

Figure 2. Right-Wink of subject A.

Figure 3. Spectrogram of (a) Left-Wink (b) Right-Wink and (c) No-Wink.
The DenseNet TL models were used to extract features from the images that were then classified by the optimised RF model. A total of 294 pipelines were developed and the best hyperparameters identified were the Gini criterion with 40 trees as well as 50 depth (or levels). It could be seen from Figure 4, that the DenseNet169 pipeline was revealed to be the best pipeline. Although the train CA for all pipelines could yield a CA of 100%, it is evident that the DenseNet169 could yield a CA of 89% for both the validation and test datasets. Whilst relatively poor test CA was observed for DenseNet 121 and DenseNet210, respectively. Table 4 depicts the performance measures of the validation dataset of DenseNet169. Conversely, Figure 5 depicts the confusion matrix of the testing dataset for DenseNet169. It could be seen that no misclassification transpired on the right-wink class, whilst one misclassification each was recorded for both the left and no-wink classes.

**Figure 4.** Classification accuracy of the evaluated pipelines.

**Table 4.** Performance measures of DenseNet169 on the validation dataset

| No.   | Class         | Precision | Recall | F1-score | CA  |
|-------|---------------|-----------|--------|----------|-----|
| Left Winking | 0             | 0.83      | 0.83   | 0.83     | 89  |
| Right Winking | 1             | 1.00      | 1.00   | 1.00     |     |
| No Winking   | 2             | 0.83      | 0.83   | 0.83     |     |

**Conclusion**

The present study evaluated different FFT-TL-optimised RF pipelines in the classification of wink-based EEG signals. It was shown from the preliminary investigation carried out, that the DenseNet 169 pipeline could attain a CA of 89% for both the validation and test datasets. The outcome of the study is non-trivial, mainly towards the realisation of a real-time BCI implementation. Future studies shall attempt on the evaluation of other TL pipelines, classifiers as well as optimisation techniques.

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