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ORIGINAL ARTICLE

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

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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.

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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

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