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The classification of EEG-based wink signals: A CWT-Transfer Learning pipeline

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Abstract

Brain–Computer Interface technology plays a vital role in facilitating post-stroke patients' ability to carry out their daily activities of living. The extraction of features and the classification of electroencephalogram (EEG) signals are pertinent parts in enabling such a system. This research investigates the efficacy of Transfer Learning models namely ResNet50 V2, ResNet101 V2, and ResNet152 V2 in extracting features from CWT converted wink-based EEG signals, prior to its classification via a fine-tuned Support Vector Machine (SVM) classifier. It was shown that ResNet152 V2-SVM pipeline could achieve an excellent accuracy on all train, test and validation datasets.

Keywords: BCI; CWT; EEG; Transfer Learning; SVM

1. Introduction

Stroke is one of the most abrupt and life-changing neurological diseases. Moreover, it is listed as the top five and ten reasons for mortality and hospitalisation respectively, in Malaysia [1]. Patients who have survived such a disease are frequently left with long term physical disabilities such as limb weakness, memory deficits, speech problems and urinary incontinence [2]. It is worth pointing out that both the upper and lower-limb motor functions are often reported to be the most affected [2–4], and, in turn, limits the patients' activities of daily living (ADL) [5]. However, the patients' motor functions may be improved through undergoing rehabilitation therapy, and Brain–Computer Interface (BCI) technology is one of the fast-growing rehabilitation technologies for post-stroke patients.

Non-invasive BCI technology is a control system that utilises brain signals into a command which controls external devices that can interact with the brain and external environment. In non-invasive BCI technology, the electrodes are placed on the scalp of the patients to collect the brain signals. The most common brain signals that are widely used and can be easily collected is electroencephalography (EEG). EEG signals are obtained through the placement of electrodes according to the International 10–20 system on the scalp. It is measured through the potential difference between the electrode and the reference electrode. This signal can be implemented to BCI-based technologies to create a smart environment for post-stroke patients. It is important to note at this juncture that information extraction is one of the most crucial aspects in BCI applications. A well-established BCI system has two essential building blocks, i.e., the identification of a significant set of EEG features and the efficacy of a given machine learning model to classify the extracted features.

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A considerable amount of studies has been carried out on the aforesaid building blocks; for instance, wink-based EEG signals have been utilised by [6] to exploit it to control prosthetic devices. The authors utilised Fast Fourier Transform (FFT) and sample range to extract the features of the collected EEG signal. The extracted features then were implemented into Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), and *k*-Nearest Neighbour (*k*NN) classification algorithms. The performance of the classifiers was evaluated through Area Under the Curve–Receiver Operating Curve (AUC–ROC) and confusion matrix. The results showed that FFT pipeline, along with LDA classifier showed the best classification accuracy (CA) of 83.3%.

Issa, Peng, You and Shah [7] investigated the classification of five emotions extracted from the frequency–time based EEG signals, i.e., sad, happy, angry, fear and disgust. The Continuous Wavelet Transform (CWT) algorithm was used to extract the Standard Deviation Vector (SDV) feature. The classification process was carried out through SVM, *k*NN, and Probabilistic Neural Network (PNN). It was shown that the polynomial kernel-based SVM classifier yielded the highest CA with 91%.

With the advancement of deep learning models, particularly Convolutional Neural Networks (CNN), researchers have employed such a technique in different fields. Nonetheless, it is worth noting that conventional CNN models often require extensive hyperparameter tuning to achieve such results and hence, researchers have exploited the use of pre-trained CNN models through transfer learning (TL). TL and its associative models have been successfully demonstrated in a myriad of applications [8–10].

Such a technique has also been utilised in the classification of sleep state EEG signals [11]. A class of TL models, i.e., ResNet was used to extract features derived from power spectral density (PSD) acquired from raw EEG signals. The features extracted were fed into the fully connected layers (herein described as conventional CNN). The proposed pipeline was compared with other pipelines, i.e., Fast Fourier Transform (FFT)-Multilayered Perceptron (MPC) as well as PSD-MPC. It was shown from the study that the PSD-ResNet-CNN model yielded the best CA of the sleep state with 87.8% for female and 83.7% for male subjects, respectively.

This study aims at evaluating the efficacy of different TL models in extracting features from EEG wink-based time-series signals that were converted into scalogram images through CWT algorithm and subsequently the classifying the features via optimised SVM as well as conventional CNN (fully connected layers) classifiers. The performance measures that were employed to evaluate the developed pipelines are CA as well as the confusion matrix.

2. Methodology

2.1. Data collection

The wink-based EEG signals were collected through a five-channel Emotiv Insight device [12]. The position of the electrodes was placed according to the International 10–20 system, at nodes AF3, AF4, T8, T7, and Pz. The signals were collected from AF3 and AF4 nodes, in which AF3 is responsible for collecting the left winking signals, whereas the AF4 is responsible for the right winking signals. The signals were collected from five healthy subjects with no history of any history of neurological diseases. The subjects were told to sit on an ergonomic chair and relax their mind before the collection of signals took place. The experiment was conducted in a circumscribed room which is located at the Faculty of Electrical Engineering Technology, University Malaysia Pahang. Prior to undertaking the investigation, ethical clearance was obtained from an institutional research ethics committee (FF-2013-327). The experiment was recorded for 60 s on each class to collect the required signals accordingly. The instructions were displayed in PowerPoint slides. It is worth to note that three classes of winking actions namely right wink, left wink and no wink, respectively were taken from each subject. For each class, the subjects were asked to repeat it six times. Therefore, the total number of samples that were acquired throughout the experiment from all the five subjects was 90.

2.2. Continuous wavelet transform (CWT)

CWT is a type of wavelet transform which consists of low and high frequencies in time series. CWT is a very effective method in pre-processing step especially in non-stationary signals such as EEG signals [13–17]. CWT provides detailed analysis of time–frequency domain via the resolutions of time and high frequencies. The original wink-based EEG signals were transformed into scalogram which is the whole value representation of the CWT coefficients of the EEG signals. The generated scalograms were resized into 224×224 in order to fit into the TL models.

2.3. Feature extraction: Transfer learning model

Transfer Learning models are pre-trained Convolutional Neural Network (CNN). These pre-trained models are popular in computer vision as it produces exceptionally accurate models [18–23]. TL models are the best solution for the lack of datasets for training the model, where it utilises the pre-trained model to train the model accordingly. The TL models that were implemented in this research are ResNet50 V2 with $7 \times 7 \times 1024$ of a flattened dimension, ResNet101 V2 and ResNet152 V2 where both the models' flattened size is $7 \times 7 \times 2048$. The weights of the TL models were frozen to extract features for the purpose of classification. In this study, the fully connected layers (FCL) that are inherent to conventional CNN models are swapped with the Support Vector Machine classifier.

2.4. Classification: SVM and CNN

Support Vector Machine (SVM) is one of the supervised Machine Learning (ML) algorithms that exploits kernel parameters to convert the input data into higher dimensional space

Table 1
Hyperparameters evaluated via grid search.

Parameters	Hyperparameters
Gamma	0.01, 0.1, 1, 10, 100
Kernel	Linear, RBF, Polynomial, Sigmoid
Regularisation	0.01, 0.1, 1, 10, 100
Degree	2, 3

through segregating the data by means of ascertaining the hyper-plane with a maximum margin [24]. The SVM classifier has been successfully implemented in a myriad of applications [24–28]. The tuning parameters of SVM are Kernel, regularisation (c), degree and gamma (γ). The kernel tricks calculated the separation adjoin in a higher dimension. The c parameter informs the algorithm the amount of misclassification that needs to be avoided in training the model. Conversely, gamma signifies the points close to the plausible lines are considered in the mathematical algorithm. The list of hyperparameters evaluated is listed in Table 1. The data was separated into three datasets, which are Training, Validation and Test datasets through a stratified ratio of 60:20:20. The best model out of 125 models developed was selected through the grid search algorithm along with five-fold cross-validation method. Grid search is used to ascertain the optimal hyperparameters of the SVM classifier employed. It is worth to mention at this juncture, that a pipeline consists of a given TL model that is paired with an optimised SVM classifier.

In order to compare the efficacy of the proposed pipeline, the conventional CNN model, in which the fully connected layers are retained was also evaluated. The same features that were extracted through TL models were fed into the fully connected layers with the first layer consists of 50 hidden neurons with the ReLu activation function. A dropout value of 0.5 is used. The output is then fed into the final hidden layer with three hidden neurons with the softmax activation function. In the present study, the Adam optimisation algorithm is used with an epoch of 50 and a batch size of ten. The performance of the pipelines was evaluated through confusion matrices and the classification accuracy (CA). The confusion matrices are used to visualise the misclassifications of the datasets [29]. The models were developed and evaluated using Spyder IDE.

3. Results and discussion

The wink-based digital signals were converted into scalogram and fed into selected TL models to extract the significant features. The extracted features were fed into the fine-tuned SVM classifier models as well as the conventional CNN models (with fully connected layers). Fig. 1 depicts the scalogram images that were obtained through CWT-Morlet wavelet algorithm.

Fig. 2 depicts the CA of all the three TL models that were classified through the conventional CNN classifier and fine-tuned SVM model. It is observed that the CA obtained through SVM pipeline obtained is better as compared to the conventional CNN pipeline. Moreover, it can be seen that the training dataset of ResNet50 V2 achieved a CA of 98%.

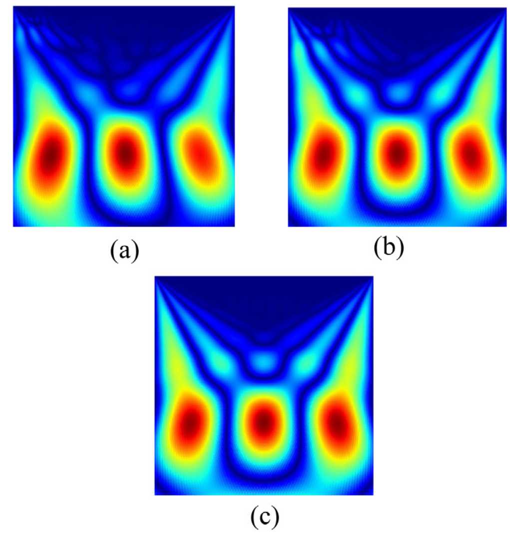

Fig. 1. Scalogram images of (a) Left Wink (b) Right Wink (c) No Wink.

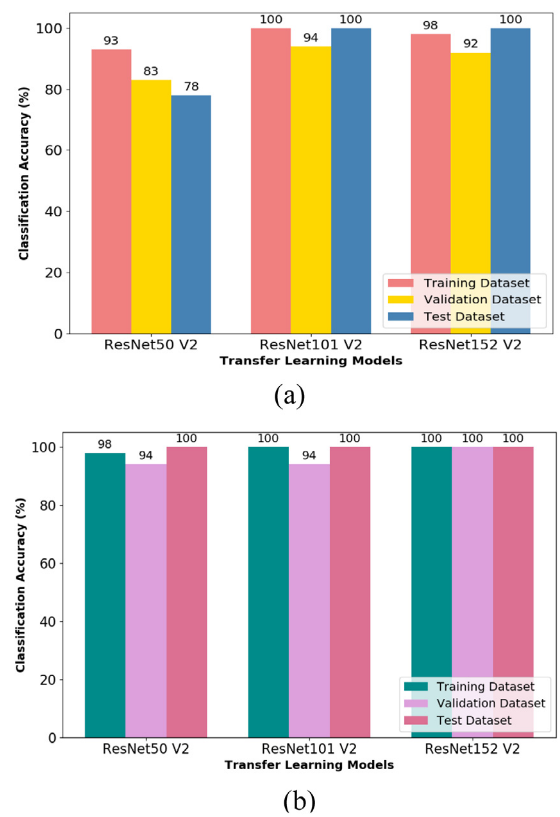

Fig. 2. Classification accuracy of evaluated (a) CWT-TL-CNN (b) CWT-TL-SVM pipelines.

Whereas, the other two TL models achieved a CA of 100% in the training phase. Through the validation dataset, it can be observed that ResNet152 V2 obtained 100% CA. Whereas, through the test dataset, all the three TL pipelines achieved 100% of CA. Therefore, it can be illustrated that ResNet152 V2-optimised SVM could classify the wink-based EEG signals better in comparison to the other pipelines evaluated.

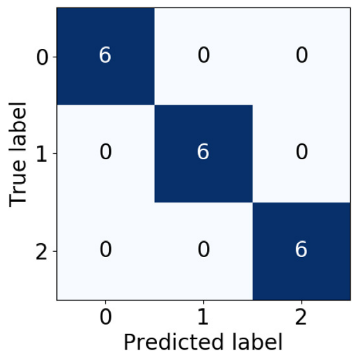

Fig. 3. Confusion Matrix of Test Dataset of ResNet152 V2 pipeline.

The hyperparameters of the best SVM model that worked along with ResNet152 V2 to achieve the highest CA identified via the grid search optimisation technique are the polynomial kernel with a quadratic degree with a gamma and regularisation value of 0.01. Fig. 3 depicts the confusion matrix of the test dataset of ResNet152 V2-SVM pipeline. It can be observed that none of the images were misclassified. The 0 represents left wink, 1 represents right wink, and 2 no wink classes, respectively.

4. Conclusion

In this study, different TL framework was proposed for the classification of wink-based EEG signals. It was demonstrated that the ResNet152 V2-SVM pipeline could yield an exceptional CA of 100%. The findings are rather promising and future work should incorporate other TL models as well as classifiers for the classification of the signals. Moreover, it indicates the possibility of the employment of the pipeline to a BCI system to control rehabilitation devices to further provide a better ADL for post-stroke patients.

CRediT authorship contribution statement

Jothi Letchumy Mahendra Kumar: Conceptualization, Writing - original draft, Methodology, Software, Investigation. **Mamunur Rashid:** Data curation, Software. **Rabiu Muazu Musa:** Visualization, Formal analysis. **Mohd Azraai Mohd Razman:** Visualization, Investigation. **Norizam Sulaiman:** Conceptualization, Resources, Project administration. **Rozita Jailani:** Methodology, Resources, Validation. **Anwar P.P. Abdul Majeed:** Conceptualization, Supervision, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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