The classification of EEG-based winking signals: A transfer learning and random forest pipeline

Jothi Letchumy Mahendra Kumar [1] , **Mamunur Rashid** [2] , **Rabiu Muazu Musa** [3] , **Mohd Azraai Mohd Razman** [1] , **Norizam Sulaiman** [2] , **Rozita Jailani** [4] , **Anwar P.P. Abdul Majeed** [Corresp. 1, 5]

[1] Innovative Manufacturing, Mechatronics and Sports Laboratory, Faculty of Manufacturing and Mechatronics Engineering Technology, Universiti Malaysia Pahang, Pekan, Pahang Darul Makmur, Malaysia

[2] Faculty of Electrical and Electronics Engineering Technology, Universiti Malaysia Pahang, Pekan, Pahang, Malaysia

[3] Centre for Fundamental and Liberal Education, Universiti Malaysia Terengganu, Kuala Nerus, Terengganu, Malaysia

[4] Faculty of Electrical Engineering, Universiti Teknologi MARA, Shah Alam, Selangor, Malaysia

[5] Centre for Advanced Innovation and Design of Embedded System, Universiti Malaysia Pahang, Gambang, Pahang, Malaysia

Corresponding Author: Anwar P.P. Abdul Majeed
Email address: amajeed@ump.edu.my

Brain Computer-Interfaces (BCI) technology plays a tremendous role in rehabilitation devices and the control of external devices for stroke patients. This is particularly due to their inability to control such devices from their inherent physical limitations after such an attack. More often than not, the control of such devices exploits electroencephalogram (EEG) signals. Nonetheless, it is worth noting that the extraction of the features and the classification of the signals is non-trivial for a successful BCI system. The use of Transfer Learning (TL) has been demonstrated to be a powerful tool in the extraction of essential features. However, the employment of such a method towards BCI applications, particularly with regards to EEG signals are somewhat limited. The present study aims to evaluate the efficiency of different TL models in extracting features for the classification of winking signals. The extracted features are classified by means of fine-tuned Random Forest (RF) classifier. The raw EEG signals are transformed into a scalogram image via Continuous Wavelet Transform (CWT) before it was fed into the TL models, namely InceptionV3, Inception ResNetV2, Xception and MobileNet. The dataset was divided into training, validation, and test datasets via a stratified ratio of 60:20:20. The hyperparameters of the RF models was optimised through the grid search approach in which the five-fold cross-validation technique was adopted. It was demonstrated from the study that the best TL model identified is the Inception ResNetV2 as it was able to yield a classification accuracy of 100% on the training dataset, through the utilisation of the optimised RF model. Moreover, similar classification accuracy was observed on both the validation and test datasets. Therefore, it could be established from the study that a comparable classification efficacy is attainable via the Inception ResNetV2 with optimised

RF pipeline. The implementation of the proposed method to a BCI system will potentially facilitate post-stroke patients to lead a better quality of life.

The classification of EEG-based winking signals: A Transfer Learning and Random Forest pipeline

Jothi Letchumy Mahendra Kumar[1], Mamunur Rashid[2], Rabiu Muazu Musa[3], Mohd Azraai Mohd Razman[1], Norizam Sulaiman[2], Rozita Jailani[4], and Anwar P. P. Abdul Majeed[1,5]

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

Corresponding Author:
Anwar P. P. Abdul Majeed[1,5]
Innovative Manufacturing, Mechatronics and Sports Laboratory, Faculty of Manufacturing and Mechatronics Engineering Technology, Universiti Malaysia Pahang (UMP), 26600 Pekan, Pahang Darul Makmur, Malaysia
Email address: amajeed@ump.edu.my

Abstract

Brain Computer-Interfaces (BCI) technology plays a tremendous role in rehabilitation devices and the control of external devices for stroke patients. This is particularly due to their inability to control such devices from their inherent physical limitations after such an attack. More often than not, the control of such devices exploits electroencephalogram (EEG) signals. Nonetheless, it is worth noting that the extraction of the features and the classification of the signals is non-trivial for a successful BCI system. The use of Transfer Learning (TL) has been demonstrated to be a powerful tool in the extraction of essential features. However, the employment of such a method towards BCI applications, particularly with regards to EEG signals are somewhat limited. The present study aims to evaluate the efficiency of different TL models in extracting features for the classification of winking signals. The extracted features are classified by means of fine-tuned Random Forest (RF) classifier. The raw EEG signals are transformed into a scalogram image via Continuous Wavelet Transform (CWT) before it was fed into the TL models, namely InceptionV3, Inception ResNetV2, Xception and MobileNet. The dataset was divided into training, validation, and test datasets via a stratified ratio of 60:20:20. The hyperparameters of the RF models was optimised through the grid search approach in which the five-fold cross-validation technique was adopted. It was demonstrated from the study that the best TL model identified is the Inception ResNetV2 as it was able to yield a classification accuracy of 100% on the training dataset, through the utilisation of the optimised RF model. Moreover, similar classification accuracy was observed on both the validation and test datasets. Therefore, it could be established from the study that a comparable classification efficacy is attainable via the Inception ResNetV2 with optimised RF pipeline. The implementation of the proposed method to a BCI system will potentially facilitate post-stroke patients to lead a better quality of life.

Keywords EEG, Winking, Continuous Wavelet Transform, Transfer Learning, Random Forest

Introduction

Stroke is a type of neurological diseases which is the third leading cause of death and the top ten cause of mortality in Malaysia. The Global Burden of Disease estimated that stroke could be the second leading cause of mortality in 2040 (Ganasegeran et al., 2019). Patients who are suffering from stroke are often left with long term impairments (Murray & Harrison, 2004). Almost all of the affected patients have various degree of neurological disorder, that is not limited to the weakening of limbs or speech impairments (Lawrence et al., 2001; Schweizer & MacDonald, 2014).

The consequences of the impairments of the limbs are the restriction of the ability to perform rudimentary activities of daily living (ADL) (Norris, Allotey & Barrett, 2012). However, rehabilitation plays a vital role in the recovering process, which helps the patients to regain their ability to be independent. In the last decade, Brain-Computer Interface (BCI) has paved its way as one of the leading technologies for rehabilitation. A BCI system essentially provides communication between the human brain signal and external devices. It facilitates the physically silent but mentally sound post-stroke patients ((Vaughan, 2003; Shih, Krusienski & Wolpaw, 2012; Lin & Hsieh, 2016). Categorically, a successful BCI primarily requires two main requirements viz. a set of electroencephalogram (EEG) features and an efficient machine-learning algorithm to classify the extracted features.

Related Works

Over the last decade, active research has been carried out on the different feature extraction and classification techniques for EEG signals (Wang et al., 2015; Salgado Patrón & Barrera, 2016; Schwarz et al., 2018; Chronopoulou, Baziotis & Potamianos, 2019; Rodrigues, Jutten & Congedo, 2019). A pre-trained convolution neural networks (CNN) (also known as Transfer Learning) was investigated to improve the BCI-system usability of a driving system which utilises EEG signals (Shalash, 2019). Online datasets were utilised in the research which was collected in a controlled lab environment through Neuro-scan data acquisition equipment with 30 effective channels and two reference electrodes. The collected EEG signals were converted into spectrogram images through the Short Time Fourier Transform (STFT) algorithm. The converted images were implemented into Alexnet TL model, which was trained via Adam optimiser with an initial rate of 0.0001. The datasets were divided into two separate datasets which are training and testing datasets with the ratio of 70:30. The results obtained showed that T3 and FP1 channels could yield reasonably high classification accuracy (CA) of 91% and 90%, respectively. It is evident from the study that TL facilitates the feature extraction process.

The detection of eye blinking from EEG signals was investigated by (Domrös et al., 2013). The intentional eye-blink EEG signals were collected through Bio-Radio device in a Biomedical Department Laboratory at the Holy Spirit University. In the research, time-domain features, i.e., maximum amplitude, minimum amplitude and the kurtosis were extracted. The extracted features were then fed into the Gaussian Radial Basis Function (GRBF) model to classify the eye blink-EEG based signals accordingly. This pipeline was compared with other models, namely, Multilayer Perceptron (MLP), Feed Forward Back Propagation, MLP-Cascade Forward Back Propagation (CFBP) and RBF Binary Classifier. The result showed that GRBF classifier performed well based on the extracted time-domain features.

Rashid et al. studied in the classification of wink based EEG signals. The features of the EEG signals were extracted through the Fast Fourier Transform (FFT) and sample range methods (Rashid et al., 2020). The FFT algorithm was utilised to transform the EEG signals into frequency domain features. The extracted features were implemented into a number of different classical machine learning classifiers, namely Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), and *k*-Nearest Neighbor (*k*NN). The results showed that LDA performed better than the other two classifiers with a CA of 83.3% and 80% for train and test dataset, respectively through the FFT features. Conversely, based on the sample range features, an identical CA was obtained through both SVM and *k*NN models, i.e., 98.9% and 96.7% for the test and train dataset, accordingly. The LDA recorded a lower CA in contrast to the aforesaid classifiers based on the sample range features; nonetheless, the CA was significantly higher compared to the FFT feature extraction technique.

Therefore, the present study focuses on the implementation of a myriad of pre-trained CNN algorithm (Transfer Learning models) to extract the features of the wink-based EEG signals. A conventional machine learning model, namely Random Forest, is implemented along with the Transfer Learning models to classify the extracted features. It is worth noting that such a pipeline has yet been investigated with regards to wink-based EEG signals. The performance of the different Transfer Learning models in feature extraction that will be classified through an optimised RF classifier shall be appraised. It is anticipated that the suggested pipeline could be implemented into a BCI assistive-technology and promote a better quality of life for post-stroke patients.

Methodology

The classification of EEG signals consists of four main steps, which are signal collection, pre-processing, feature extraction and classification. This research aims to classify wink-based EEG signals through Transfer Learning models and fine-tuned RF classifier. A five-channel Emotiv Insight EEG device was used to collect the wink-based EEG signals (Heunis, 2016). The position of the channels is placed according to the International 10-20 system, and the channels are placed at node AF3, AF4, T7, T8 and Pz.

The wink-based EEG signals were collected from five healthy subjects aged between 22 till 29 years old. The five subjects consist of three males and two females. The subjects that were chosen was ascertained not to have any medical problem and have normal vision. Moreover, it is worth noting that the subjects did not have any history of neurological diseases. A written informed consent form was recieved from the subjects participated in the present study. The subjects were told to relax and sit on an ergonomic chair in a circumscribed room which is located at Faculty of Electrical Engineering Technology, University Malaysia Pahang. These steps were taken to avoid external signals to be recorded. The ethical approval for this study was obtained through an institutional research ethics committee provided by Universiti Kebangsaan Malaysia (FF-2013-327).

The subjects were instructed through slide show displayed on LCD. The experiment paradigm shown in Fig. 1 were used to collect the required signals. The collection starts with the first five seconds of a resting-state, followed by winking action for the next five second. This step is continued to obtain six samples of winking signals. Left and Right winking action were run separately, and both of them were recorded for 60 seconds (one minute).

Figure 1: The experiment Paradigm for EEG signal acquisition

Continuous Wavelet Transform (CWT)

Continuous Wavelet Transform (CWT) is the representation of the time-frequency domain of a set of signals collected. CWT is one of the most effective methods used in medical fields which consists of non-stationary signals such as EEG, electromyography (EMG) or electrocardiogram (ECG) amongst others. The resolution represented through CWT algorithm has been reported to advantageous due to the utilisation of the small scale of high frequencies and large scale of low frequencies (Türk & Özerdem, 2019). Moreover, it has also been reported to provide a better representation of the arrangement of the frequency domain features as compared to Fourier Transforms. The mother wavelet that was utilised in this research is the Morlet Wavelet. Morlet wavelet is the multiplication of the complex exponential and Gaussian window. Morlet wavelet method is widely used in the medical field, which consists of non-stationary signals (Qassim et al., 2012). The Morlet algorithm gives an instinctive link between frequency and time domain to distinguish the signals acquired via Fourier Transform.

Feature Extraction: Transfer Learning (TL)

TL models are widely used in computer vision field primarily owing to its ease in CNN model development, especially omitting the notion of building the model from scratch (as pre-trained models are used) and hence reduces the model development time (Amanpour & Erfanian, 2013; Chronopoulou, Baziotis & Potamianos, 2019). The use of TL models is also advantageous in the bioinformatic related domains as data is often scarce, and it has been demonstrated in the literature that TL models are able to work with limited dataset. Table 1 illustrates the TL models and the parameters that were implemented in the present study. It is worth mentioning that the TL models used in the study are used only for feature extraction where only the convolutional layers are exploited. In contrast to a full pre-trained CNN model, the fully connected layers (dense layers) are replaced with a traditional machine learning classifier in the study, which in this case, the Random Forest classifier is employed.

Table 1: List of TL models and its respective parameters implemented in this research

Classifier: Random Forest (RF)

Random Forest (RF), also known as Random Decision Forests, is a supervised machine learning algorithm that evolved through the ensemble of multiple Decision Tree classifiers. It is also known as one of the many bagging-type ensemble classifiers. The combination of a few decision trees to mitigates the notion between the variance and bias, which in turn reduces the possibility of overfitting to transpire. It is worth noting that the RF classifier has been widely used in many different medical oriented types of research (Cherrat, Alaoui & Bouzahir, 2020; Tabares-Soto et al., 2020). The RF hyperparameters evaluated in this study are the number of trees (n_estimators), depth of the trees (max_depth), and the measurement of the splitting quality (criterion). The hyperparameters of the RF models were tuned via the grid search algorithm through the five-fold cross-validation technique. Table 2 lists the hyperparameter values of RF classifiers appraised. A total of 98 RF models were investigated in this research for four different transfer learning models (conclusively, a total of 392 TL pipelines were evaluated) towards its efficacy in classifying the wink-based EEG signals. Figure 2 depicts the complete pipeline developed in this study. The developed pipelines (different TL models with its associated optimised RF models) was analysed and evaluated using a Python IDE, specifically Spyder 3.7.

Table 2: Hyperparameter of the RF models evaluated

Figure 2: The complete TL pipeline

.

Performance Evaluation

The confusion matrix is one of the most straightforward and simplest measures used to determine model consistency and correctness (Sokolova & Lapalme, 2009; Flach, 2019). The classification models employed in this study are assessed by means of classification accuracy (CA), precision, recall, and f1-score. The accuracy is simply the ratio between the number of accurately predicted observations and the total number of observations. The precision measures the percentage of correct positive forecasts over the cumulative number of positive forecasts. The recall (often known as sensitivity) is the number of true positive predictions divided by the sum of true positives as well as the false negatives (Vijay Anand & Shantha Selvakumari, 2019). The f1-score discloses the balance between the recall and the precision values.

Experimental Results and Discussion

The wink-based EEG signals were extracted through the single-channel Emotiv device at the sampling rate of 128Hz. The digital signals were then converted into scalogram via CWT. The images were divided into three groups of datasets which are training, validation and test datasets through a stratified ratio of 60:20:20. The stratification ensures that the datasets are equally divided amongst the evaluated classes. The images were then fed into the TL models and classified through optimised RF models. Figure 3 and Figure 4 depicts the raw and scalogram transformed images of the wink classes.

Figure 3: Plot of raw EEG signal (A) Left-Wink (B) Right-wink and (C) no-wink

Figure 4: Scalogram of (A) Left Wink (B) Right Wink (C) No Wink

Figure 5: Classification Accuracy of TL pipelines

Figure 5 depicts that Inception ResNetV2 TL pipeline demonstrated the best CA amongst other evaluated pipelines on all train, validate and test datasets. A similar performance is illustrated by the Inception V3, and MobileNet TL pipelines, in which both achieved a CA of 100% on the training dataset, whilst for the validation and test datasets, a CA of 94% was observed. Conversely, the Xception TL pipeline performed better than the aforementioned two pipelines as it yielded a CA of 100% on the test dataset. Therefore, it is evident that the Inception ResNetV2 transfer learning model coupled with an optimised RF classifier is able to yield exceptional classification on the different wink-based EEG signals evaluated. The optimised RF hyperparameters that augur well with the Inception ResNetV2 transfer learning model are 10, 20 and Gini impurity for the number of trees, depth of trees and criterion (a measure of split quality), respectively. Table 3 tabulates the performance measure of the testing dataset based on the Inception ResNetV2 pipeline. Figure 6 illustrates the confusion matrix of the validation dataset in which 0, 1 and 2 represent the left, right and no wink classes.

Table 3: Performance Matrix of Inception ResNetV2

Figure 6: Confusion Matrix of Validation Dataset of Inception ResNetV2

The efficacy of pre-trained CNN models have been demonstrated in the literature, for instance, Kant et al. implemented a CWT algorithm to classify motor imagery signals by means of transfer learning models (Kant et al., 2020). The digital EEG signals were converted into two-dimensional scalogram images that were fed into different pre-trained CNN models such as AlexNet, VGG16 and VGG19 to recognise the motor imagery signals of the Left- and Right-hand movements. It was shown from the study that the employment of such a technique could achieve a CA of 97.06%. In a different study, CWT transformation has been utilised along with a pre-trained CNN model, SqueezeNet to classify sleep stage based on EEG signals (Jadhav et al., 2020). It was demonstrated that the pipeline could yield exceptional CA. It is apparent that through the conversion of signals via CWT could provide meaningful features to be extracted through the transfer learning approach, which was also demonstrated through the present study. It is also worth noting that with regards to the classification of wink-based EEG signals, the present study has shown that exceptional classification was achieved via the proposed approach and was shown to be better than that of results reported by Rashid et al. (Rashid et al., 2020).

Conclusion

It could be shown from the present investigation that the employment of Transfer Learning is a rather promising approach in improving the performance of EEG classification for BCI applications. Different stages of winking were converted into a spectrogram image through CWT. It has been demonstrated through the study that the Inception ResNetV2 could extract significant features for the wink-based EEG signals as compared to the other TL models. In addition, it is also worth noting that the role of hyperparameter tuning could not be simply overlooked as it could further improve the performance of the evaluated classifier, herein, the RF for the present investigation. Future works shall evaluate the performance of other forms of classifiers and its combination with the evaluated TL models on such classification.

Acknowledgements

This work was supported by Universiti Malaysia Pahang [grant number RDU180321].

References

Amanpour B, Erfanian A. 2013. Classification of brain signals associated with imagination of hand grasping, opening and reaching by means of wavelet-based common spatial pattern and mutual information. *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*:2224–2227. DOI: 10.1109/EMBC.2013.6609978.

Cherrat E, Alaoui R, Bouzahir H. 2020. Convolutional neural networks approach for multimodal biometric identification system using the fusion of fingerprint, finger-vein and face images. *PeerJ Computer Science* 2020:1–15. DOI: 10.7717/peerj-cs.248.

Chronopoulou A, Baziotis C, Potamianos A. 2019. An Embarrassingly Simple Approach for Transfer Learning from Pretrained Language Models. :2089–2095. DOI: 10.18653/v1/n19-1213.

Domrös F, Störkle D, Ilmberger J, Kuhlenkötter B. 2013. Converging Clinical and Engineering Research on Neurorehabilitation. *Converging Clinical and Engineering Research on Neurorehabilitation* 1:409–413. DOI: 10.1007/978-3-642-34546-3.

Flach P. 2019. Performance Evaluation in Machine Learning: The Good, the Bad, the Ugly, and the Way Forward. *Proceedings of the AAAI Conference on Artificial Intelligence* 33:9808–9814. DOI: 10.1609/aaai.v33i01.33019808.

Ganasegeran K, Fadzly M, Jamil A, Sivasampu S. 2019. Discover! Malaysia's Stroke Care Revolution - Special Edition. *ResearchGate* 2:1–32.

Heunis C. 2016. Export and Analysis of Emotiv Insight EEG Data via. :1–11. DOI: 10.13140/RG.2.1.3081.4326.

Jadhav P, Rajguru G, Datta D, Mukhopadhyay S. 2020. Automatic sleep stage classification using time–frequency images of CWT and transfer learning using convolution neural network. *Biocybernetics and Biomedical Engineering* 40:494–504. DOI: 10.1016/j.bbe.2020.01.010.

Kant P, Laskar SH, Hazarika J, Mahamune R. 2020. CWT Based Transfer Learning for Motor Imagery Classification for Brain computer Interfaces. *Journal of Neuroscience Methods* 345:108886. DOI: 10.1016/j.jneumeth.2020.108886.

Lawrence ES, Coshall C, Dundas R, Stewart J, Rudd AG, Howard R, Wolfe CDA. 2001. Estimates of the prevalence of acute stroke impairments and disability in a multiethnic population. *Stroke* 32:1279–1284. DOI: 10.1161/01.STR.32.6.1279.

Lin JS, Hsieh CH. 2016. A Wireless BCI-Controlled Integration System in Smart Living Space for Patients. *Wireless Personal Communications* 88:395–412. DOI: 10.1007/s11277-015-3129-0.

Murray CD, Harrison B. 2004. The meaning and experience of being a stroke survivor: An interpretative phenomenological analysis. *Disability and Rehabilitation* 26:808–816. DOI: 10.1080/09638280410001696746.

Norris M, Allotey P, Barrett G. 2012. "It burdens me": The impact of stroke in central Aceh, Indonesia. *Sociology of Health and Illness* 34:826–840. DOI: 10.1111/j.1467-9566.2011.01431.x.

Qassim YT, Cutmore T, James D, Rowlands D. 2012. FPGA implementation of Morlet continuous wavelet transform for EEG analysis. *2012 International Conference on Computer and Communication Engineering, ICCCE 2012*:59–64. DOI: 10.1109/ICCCE.2012.6271152.

Rashid M, Sulaiman N, Mustafa M, Bari BS, Sadeque MG, Hasan MJ. 2020. Wink based facial expression classification using machine learning approach. *SN Applied Sciences* 2:183.

Rodrigues PLC, Jutten C, Congedo M. 2019. Riemannian Procrustes Analysis: Transfer Learning for Brain-Computer Interfaces. *IEEE Transactions on Biomedical Engineering* 66:2390–2401. DOI: 10.1109/TBME.2018.2889705.

Salgado Patrón J, Barrera C. 2016. Robotic arm controlled by a hybryd brain computer interface. *ARPN Journal of Engineering and Applied Sciences* 11:7313–7321.

Schwarz A, Ofner P, Pereira J, Sburlea AI, Müller-Putz GR. 2018. Decoding natural reach-and-grasp actions from human EEG. *Journal of Neural Engineering* 15. DOI: 10.1088/1741-2552/aa8911.

Schweizer TA, MacDonald RL. 2014. *The behavioral consequences of stroke*. DOI: 10.1007/978-1-4614-7672-6.

Shalash WM. 2019. Driver Fatigue Detection with Single EEG Channel Using Transfer Learning. *IST 2019 - IEEE International Conference on Imaging Systems and Techniques, Proceedings*:1–6. DOI: 10.1109/IST48021.2019.9010483.

Shih JJ, Krusienski DJ, Wolpaw JR. 2012. Brain-computer interfaces in medicine. *Mayo Clinic Proceedings* 87:268–279. DOI: 10.1016/j.mayocp.2011.12.008.

Sokolova M, Lapalme G. 2009. A systematic analysis of performance measures for classification tasks. *Information Processing and Management* 45:427–437. DOI: 10.1016/j.ipm.2009.03.002.

Tabares-Soto R, Orozco-Arias S, Romero-Cano V, Bucheli VS, Rodríguez-Sotelo JL, Jiménez-Varón CF. 2020. A comparative study of machine learning and deep learning algorithms to classify cancer types based on microarray gene expression data. *PeerJ Computer Science* 2020:1–22. DOI: 10.7717/peerj-cs.270.

Türk Ö, Özerdem MS. 2019. Epilepsy detection by using scalogram based convolutional neural network from eeg signals. *Brain Sciences* 9. DOI: 10.3390/brainsci9050115.

Vaughan TM. 2003. Brain-computer interface technology: A review of the Second International Meeting. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 11:94–109. DOI: 10.1109/TNSRE.2003.814799.

Vijay Anand S, Shantha Selvakumari R. 2019. Noninvasive method of epileptic detection using DWT and generalised regression neural network. *Soft Computing* 23:2645–2653. DOI: 10.1007/s00500-018-3630-y.

Wang H, Dong X, Chen Z, Shi BE. 2015. Hybrid gaze/EEG brain computer interface for robot arm control on a pick and place task. *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS* 2015-Novem:1476–1479. DOI: 10.1109/EMBC.2015.7318649.

Figure 1

The experiment Paradigm for EEG signal acquisition

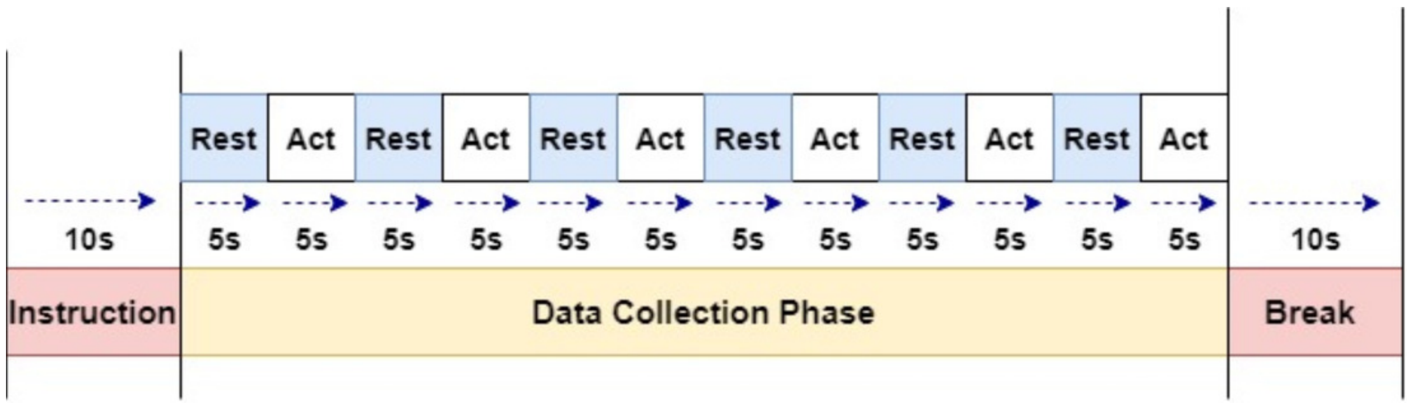

Figure 2

The complete TL pipeline

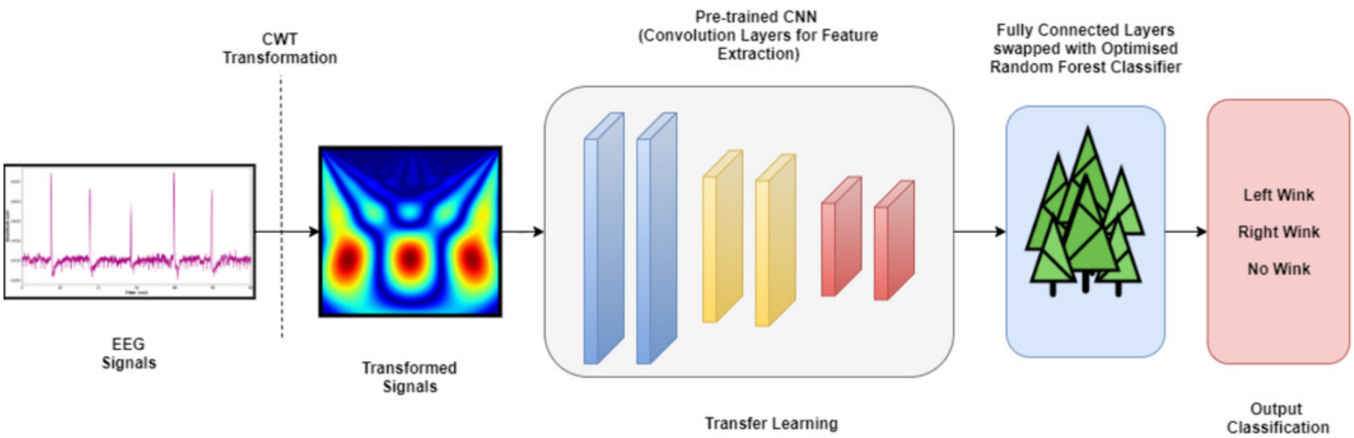

Figure 3

Plot of raw EEG signal (A) Left-Wink (B) Right-wink and (C) no-wink

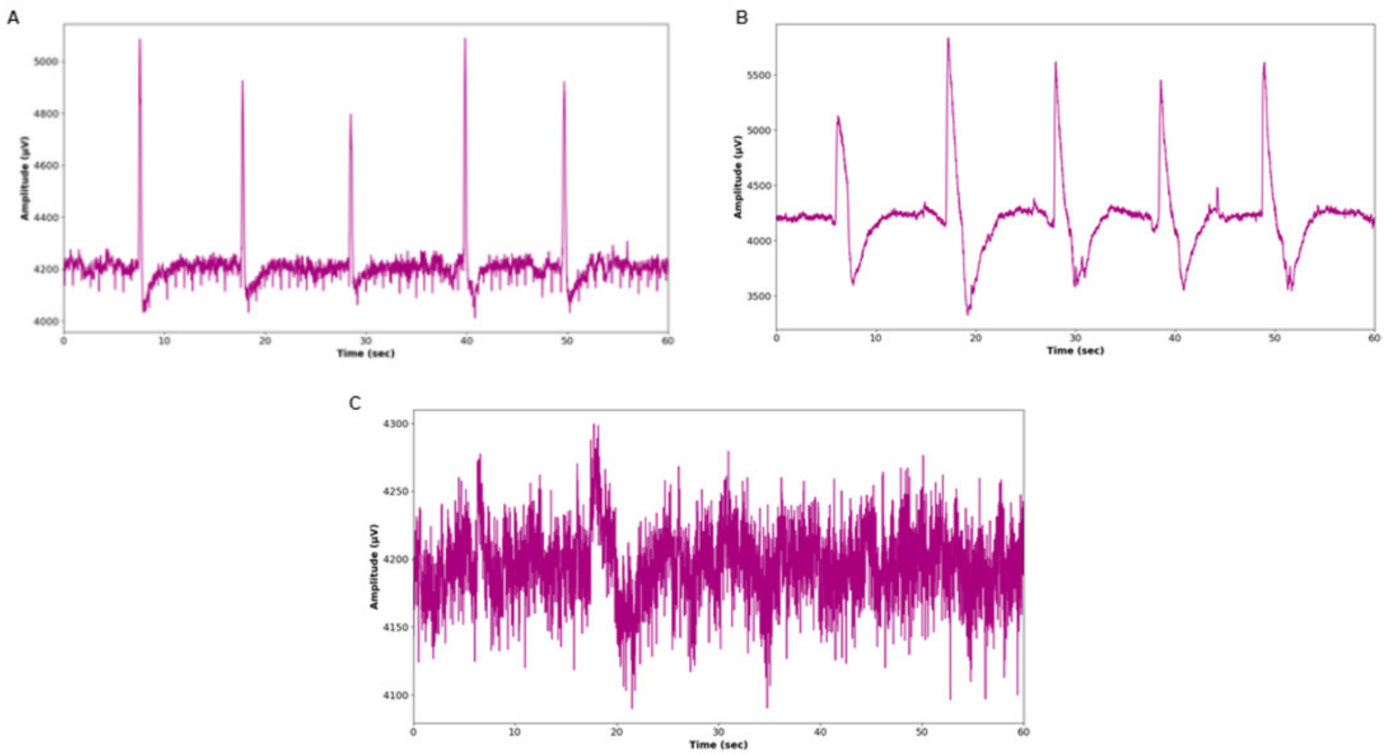

Figure 4

Scalogram of (A) Left Wink (B) Right Wink (C) No Wink

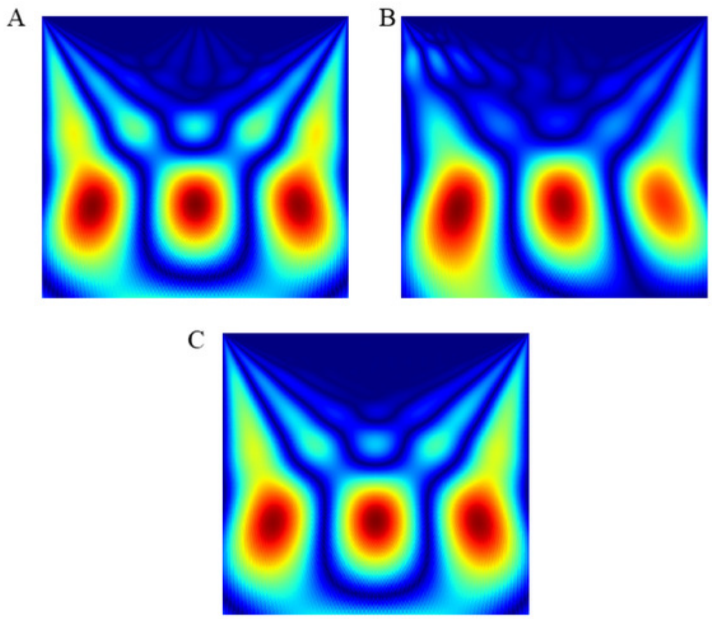

Figure 5

Classification Accuracy of TL pipelines

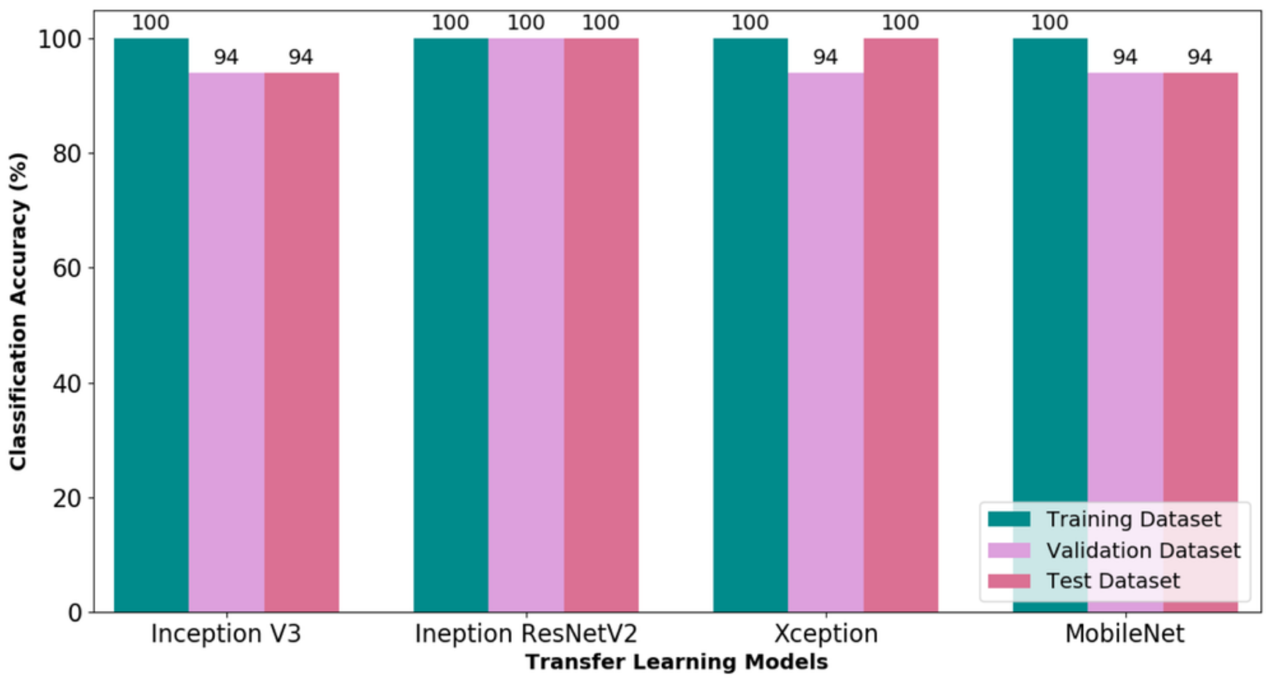

Figure 6

Confusion Matrix of Validation Dataset of Inception ResNetV2

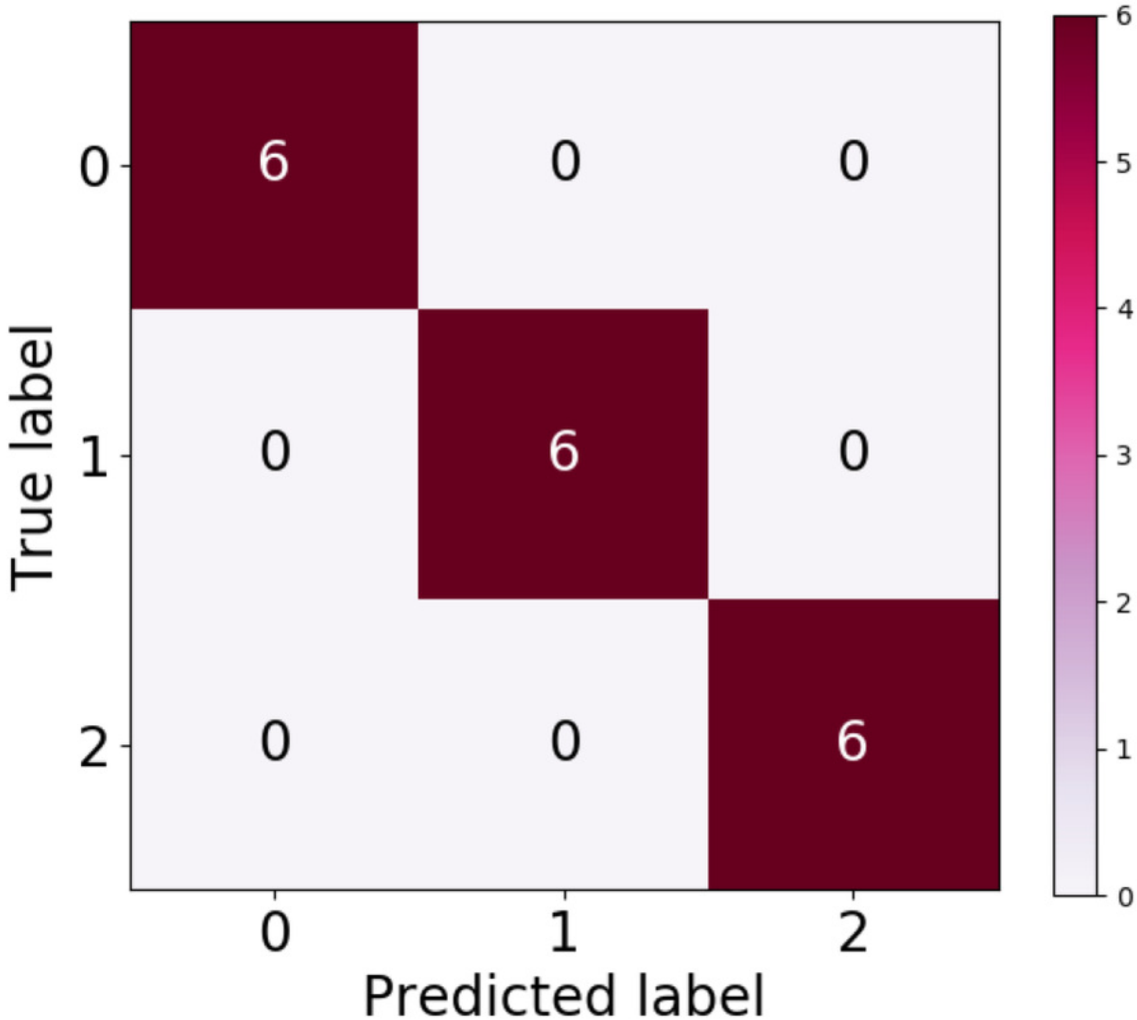

Table 1(on next page)

List of TL models and its respective parameters implemented in this research

Table 1:

List of TL models and its respective parameters implemented in this research

No.	Transfer Learning Models	Flatten Size	Input Image Size
1	Inception V3	8*8*2048	299*299
2	Inception ResNetV2	8*8*1536	299*299
3	Xception	10*10*2048	299*299
4	MobileNet	7*7*1024	224*224

Table 2 (on next page)

(on next page)

Hyperparameter of the RF models evaluated

Table 2:

Hyperparameter of the RF models evaluated

No.	Hyperparameters	Hyperparameter values
1	Number of Trees	10, 20, 30, 40, 50, 60, 70
2	Depth of Trees	10, 20, 30, 40, 50, 60, 70
3	Criterion	Gini and Entropy

Table 3(on next page)

Performance matrix of Inception ResNetV2

Table 3:

Performance Matrix of Inception ResNetV2

Class	Represented Class	Precision	Recall	F1-score	CA
Left Winking	0	1.00	1.00	1.00	
Right Winking	1	1.00	1.00	1.00	1.00
No Winking	2	1.00	1.00	1.00	