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ORIGINAL ARTICLE

The Classification of EEG-based Winking Signals: A Transfer Learning and Random Forest Approach

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ABSTRACT – Brain Computer-Interfaces (BCI) offers a means of controlling prostheses for neurological disorder patients 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 Electroencephalogram (EEG) signals. Nonetheless, it is worth noting that the extraction of the features is often an arduous task. 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 evaluate the efficacy of different TL models in extracting features for the classification of winking. The extracted features are classified utilizing an optimized 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 hyperparameters of the RF model was optimized through the grid search approach. A five-fold cross-validation technique was employed on the processed dataset that was split into training, testing, and validation with a stratified ratio of 60:20:20. It was demonstrated from the study that the best evaluated TL model identified is DenseNet169 as compared to DenseNet121 and DenseNet201.The overall validation and test accuracy attained through the DenseNet169 model is approximately 89%. It can be suggested that the proposed pipeline is suitable to classify wink-based EEG signals for BCI hand grasping application.

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Introduction

The Institute for Health Metrics and Evaluation (2017) reported that the stroke leads as the third cause of mortality in Malaysia. Whereas, Global Burden of Disease Report (2016) that the stroke will be the second leading cause of mortality in 2040 [1]. It is the list of top ten leading root of fatality rate and also the reason for hospitalization in Malaysia. World Health Organization (WHO) annouced the need for rehabilitation for post stroke patients as the demographic and health trends are increasing [2].

Stroke is one of the most common neurological disease [3]. The main reason of stroke is the blockage or bust of the blood vessels that carries oxygen and nutrients to the brain [4]. The most fundamental building block of a nervous's system is the neuron. These neurons are specialised in the conveyance of the information all over the body. The collection of all this neurons that are interconnected represents the human behavior and action. Neuromuscular system is the merge of the nervous system and muscles that works together which allows the movements [5]. The dysfunctional of the neurons breaks the contact between the nervous system and muscles. The other main function of those neurons are the informative signals that generates within the neurons. These brain signals represents the every actions of a human body.

Brain signals could be monitored through different techniques, namely Electroencephalography (EEG), Electrocorticography (ECoG), Magnetic Resonance Imaging (MRI), functional Magnetic Resonance Imaging (fMRI) and Positron Emission Tomography (PET) [6]. These scientific techniques help us better understand the function of the human brain. Due to its excellent temporal resolution, non-invasive, usability and low set-up costs, EEG is the most common method for capturing brain signals [7], [8].

EEG is increasingly relevant in the diagnosis and treatment of neurodegenerative diseases and defects in the brain. A classification's main purpose is to

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distinguish EEG segments and to evaluate if people are healthy or to measure a subject's mental state relevant to a task being performed [10]. Normally enormous amounts of data are produced by EEG and visual inspection to discriminate against EEG is a time-consuming, error-prone, expensive process and not enough for reliable information. The development of automated EEG classification methods is therefore crucial to ensure proper evaluation and treatment of neurological diseases [9].

In April 2013, the Obama administration announced the launch of the BRAIN (Brain Research through Advancing Innovative Neurotechnology). The BRAIN initiates the potential to do for neuroscience what the Human Genome Project did for genomics by supporting the development and application of innovative technologies which includes the Brain-Computer Interface (BCI) that can create a dynamic understanding of brain function [10].

Related Work

Various approaches to the classification of EEG signals in different research have been published up to this point, and various classification accuracies for EEG data have been published in the last decade [13–16].

Detection of intentional eye blink through EEG signals was investigated by [11]. The intentional eye blinking signals were collected using the Bio-Radio device. The signals were acquired in the Biomedical Department Laboratory at the Holy Spirit University. The signals collected are segmented into windows with 480 samples through a boxcar window. The authors have extracted time domain features to classify the EEG 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 has been implemented with RBF. The RBF used has three layers of the network. They have implemented Gaussian Radial Basis Function to classify the EEG signals accordingly. A comparison between other classifiers has been done by the authors. They have compared between multilayer perceptron (MLP) with Feed Forward Back Propagation (FFBP), MLP-Cascade Forward Back Propagation (CFBP) and RBF Binary Classifier. The results for all the three classifications were 96.68%, 99.83%, and 100% respectively on each classifier.

[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. Database for Emotion Analysis using Physiological Signals (DEAP) and MAHNOB human-computer interface (MAHNOB-HCI) to evaluate their method. Besides, they also performed an online experiment to make their method more robust. They experimentally demonstrated that our method produces state-of-the-art results in terms of binary valence/arousal classification, based on DEAP and MAHNOB-HCI datasets. Besides this, for the online experiment, the study achieved 69.75% accuracy for the valence space and 70.00% accuracy for the arousal space after fusion, each of which has surpassed the highest performing single modality (69.28% for the valence space and 64.00% for the arousal space). The results suggest that the combination of facial expressions and EEG information for emotion recognition compensates for their defects as single information sources.

[13] developed a deep learning-based method that automatically exploits the time-frequency spectrum of the EEG signal, removing the need for manual feature extraction. Using CWT they have extracted the time-frequency spectrogram for EEG signal of 10 healthy subjects and converted to RGB images. The images were classified using transfer learning of a pre-trained Convolutional Neural Network (CNN), Alexnet. The proposed method was evaluated using a publicly available dataset, an open-access comprehensive ISRUC-Sleep dataset. The main advantage of this method is eliminating the need for manual feature extraction and selection while taking advantage of the advancements in the deep image classification domain. High-resolution time-frequency spectrograms of sleep epochs were extracted using CWT and converted to RGB images. The extracted images were intuitive and interpretable according to AASM guidelines. These images were fed to pre-trained CNN, AlexNet. The overall accuracy achieved is 84%.

To the best of the authors' knowledge, the capability of a hybrid Transfer Learning (TL) – Random Forest (RF) pipeline in classifying wink-based EEG signals has yet been investigated. Therefore, the objective of this paper is to evaluate the efficacy of different TL models in extracting features that are classified by an optimized RF model. It is hypothesized that the proposed technique could distinguish different categories of EEG signals attained from winking expressions. The outcome of this study should help to improve the patients' daily lives quality by implementing BCI [8], [14], [15]. A detailed methodology of this process is provided in the subsequent section.

Methodology

Typically, the classification of EEG signals consists of four steps, namely signal collection, pre-processing, 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 to extract the image-based features and RF Machine Learning (ML) models.

In developing such a system, EEG Emotiv Insight (EI) Mobile device was used to collect the EEG signals of eye winking. EI has its interface communication program and records the EEG signal that can be analyzed. Emotive Insight (EI) is a smooth and glossy device to collect certain signals of the electrical signal produced by the neurons of the brain while conducting certain actions. This device consists of 5 channels including the reference channel [26]. Insight has advanced electronics that are fully optimized to produce clean, robust signals any time and it can be used anywhere due to its mobility property [18].

EI is specially designed to measure certain types of electrical signals produces through the nodes of the brain neurons. It measures and tracks the focus, engagement, interest, excitement, relaxation and stress levels. Insight mainly detects facial expressions such as blink, wink, frown, surprise, and smile. The aforesaid 5 channels are AF3, AF4, T7, T8, and Pz, respectively. The position of these nodes was determined according to the international standardized 10-20 system. The position of the electrodes as shown in Figure 1.

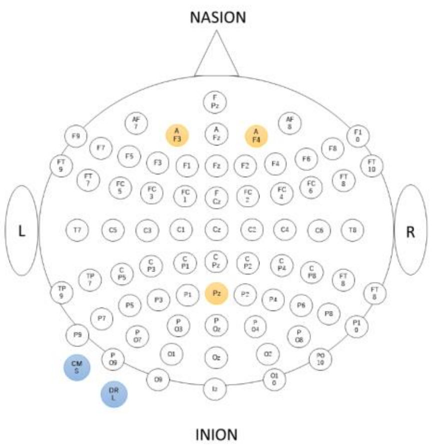


Figure 1. Position of the Electrode

To participate in this experiment, five healthy subjects were selected. The participants were 3 males and 2 females aged 22 to 29. All of them are undergraduate students. The subjects have been reported to have no medical problems and have normal vision. The participants have no history of neurological disease or psychiatric disorder. None of them have any prior experience in the experiment that will be carried out. Besides, the subjects were not aware of the Brain-Computer Interface (BCI) applications. The study has been aproved 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, University 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 without any extra physical activity throughout the experiment. The slide show demonstration was shown as a guide for the participants to obey and perform the experiment appropriately. The slides were shown almost one meter away from the subject.

Throughout the experiment, a model that consists of five left and right wink trials was used.The experiment paradigm is shown in Figure 2. 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 kinds of winking action for one minute.

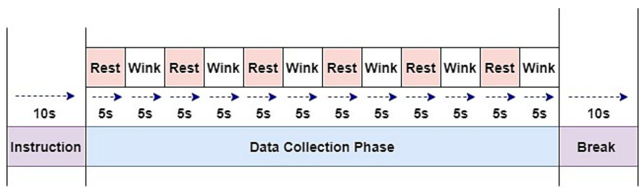


Figure 2. The experiment Paradigm for EEG signal

The pre-process of EEG datasets can be carried out in time domain, frequency domain, and time-frequency domain. It is possible to reflect the signal obtained from the electrodes in the time or frequency domain. Evaluation of the signal characteristics in time domain representation is very complicated, but it could be studied in frequency domain representation. 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 contains a compromise between time resolution and frequency resolution [19]. It is a visualization 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 color or brightness. Using the FFT to create a spectrogram is a digital process. In the time domain. Digitally sampled data is separated into segments that normally overlap, and FFT to measure 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:

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

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)

Inadequate training data is a serious issue in all bioinformatics related domains. The use of TL could minimize this issue [23], [24]. TL is a popular method in computer vision as it allows for the development of accurate models in a time-effective way [25]–[27]. Instead of initiating the learning process from scratch, TL starts from trends learned while solving various problems (pre-trained models), besides, classification leverages from previous experience [28]. This technique should support from pre-trained models in the classification leverages. The models used 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	

Classifier: Random Forest (RF)

Random Forest (RF) is an ensemble learning method for classification, regression, and other tasks, In which a number of decision trees are created at the training time and a class is given as output which is the mode of the classes [29]. In order to create number of decision trees, data and variables are selected randomly from the available set of data and variables. To build a tree during training time a finite set of thresholds is used among which a threshold is selected for each node. While constructing a tree separation of classes is being done and probability of data point to be of any class is different for each node. The newly arrived data point goes down in the tree and it ends at leaf and the class with highest probability for that node shows the actual class of data point in that tree. Single random tree is not a good classifier but if we combine a number of random trees then it becomes a very good classifier [30]. The Gini value of the Gini index is used as the basis of the splitting node. The hyperparameters of RF will be number of estimators, maximum features, maximum depth, minimum samples split, minimum sample leaf, Bootstrap, and criterion. Table 2. illustrates the hyperparameters that were tuned through grid search method.

Table 2. List of hyperparameters values in RF classifer

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

Cross-Validation Strategy

Owing to the limited set of data, the k-fold cross-validation technique is employed. This approach provides ample data for model training and also leaves adequate data for test and validation. k-fold cross-validation solves this issue. In k-fold cross-validation, the data is divided into k subsets. Through this method, the cross-validation is repeated k times, such that each time, one of the k subsets is used as the test and validation dataset and the other k-1 subsets are put together to form a training set. Such technique has been reported to reduces bias [31]–[33].

In this research, each dataset was classified into three dataset classes which are train dataset, validating dataset and testing dataset [34]. The train data group has been used to train the prediction model. Whereas, the validate data group has been utilized to evaluate the model and test dataset used to measure the classifier's performance. As a general rule and empirical evidence, K = 5 or 10 is generally preferred. Therefore, K = 5 was chosen. Ninety (90) instances have been randomly categorized into 5 subgroups and one of the five subgroups was provided as test data for each experiment, while the other nine are used as the training data. Then, the average efficiency is determined over all the folds. RF models performance was analyzed and measured using Spyder 3.7.

Performance Evaluation

Using the confusion matrix is a simple and unambiguous way to present the statistical effects of a classifier. The confusion matrix is one of the most straightforward and simplest measures used to determine model consistency and correctness [35], [36]. Table 3 illustrated the truth table of confusion matrix.

Table 3. The Confusion Matrix

PREDICTED \ ACTUAL	Posituves (1)	Negatives (0)
Positives (1)	TP	FP
Negatives (0)	FN	TN

The classification models employed in this study are assessed by means of classification accuracy, precision, recall, and f1-score. The accuracy is simply the correlation between the number of observes reasonably listed and the total number of observations. The precision measures the percentage of correct positive forecasts over the cumulative number of positive forecasts. The recall is the number of True Positives the number of False Negatives. It is the number of positive predictions divided by the number of positive class values in the test data [37].

Experimental Resuls and Discussion

As mentioned earlier, this chapter refers to the collected data sets for the proposed method. The proposed approach is being used to classify EEG signals of the winking tasks of three classes. The results of the experimental data sets will be discussed below.

The EEG winking data consists of six sets having two single-channels 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 signal has been converted to an image. The converted images were saved into 224 × 224 dimension as per the input size for the TL models. The bar chart below illustrates the accuracy result of all the TL models classified with the fine-tuned RF classifier. Figure 3 shows the plot of raw data of five trials of the EEG Right Winking signal of subject A. Whereas, Figure 4 shows the spectrogram of the converted digital signal.

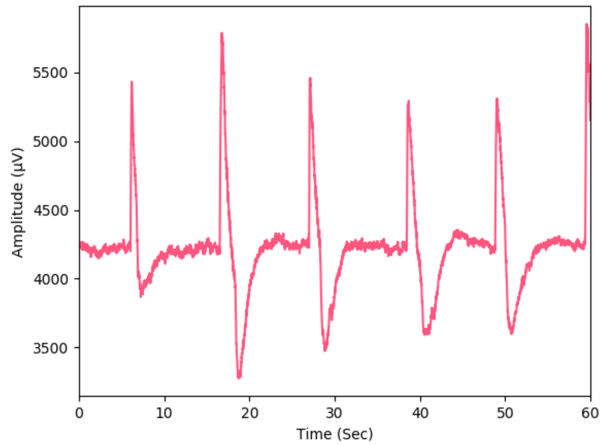


Figure 3. Right Winking of Subject A

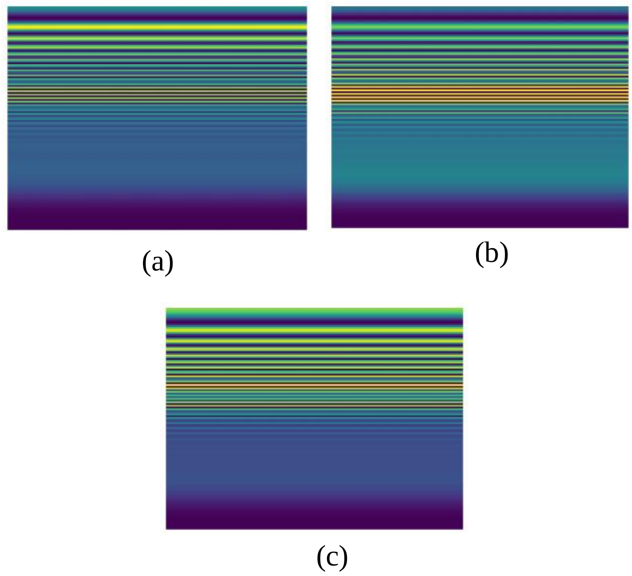
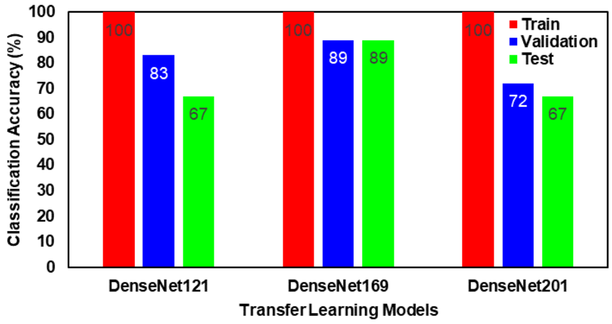


Figure 4. Spectrogram of (a) Left Wink (b) Right Wink (c) No-Wink

The TL models were used to extract features and select suitable features from the images. The outcome from TL models was for classification research on the hyperparameter tuned RF model. The grid-search method was used to tune the hyperparameters of the RF model. A total of 98 RF models were developed through varying the hyperparameters of the RF algorithm. The parameters that were tuned are the maximum depth, number of trees, and the criteria of the classifier. The best type of criteria that was used to simulate the model is Gini Index. The number of trees that performed the best is 40. Whereas, the maximum number of levels in each decision tree is 50 obtained the highest accuracy.

Through Figure 5, DenseNet169 discloses the best model among all the other TL models. It is noticeable that by trying to run the classification on training datasets, all the three TL models achieved 100%



accuracy. The average CA on the validation and testing dataset of the DenseNet169 pipeline is

Figure 5. Classification accuracy of TL Models

approximately 89%, suggesting that this pipeline is the best amongst the evaluated models. Table 4 depicts the performance measures of the validation dataset of DenseNet169.

Table 4. Performance measures of DenseNet169 of the Validation dataset

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

The following Figure 6 show the confusion matrix of the testing dataset of DenseNet169.

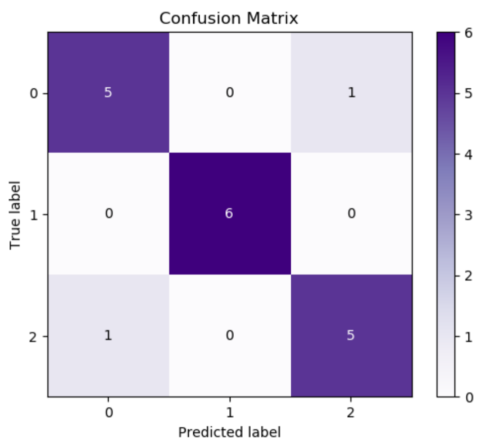


Figure 6. Confusion Matrix of Testing Dataset

Conclusion

Transfer Learning is a promising approach to improve EEG classification performance in BCI. In this paper, the transfer learning method using imagenet is employed to classify winking stages automatically. Different stages of winking were converted into a spectrogram image through FFT. This research focused on implementing different types of TL models along with the spectrogram. The main purpose of the TL models is to extract features and select the best features to classify the EEG signal accordingly. The features then implemented into the RF classifier to classify the signals accordingly. Through this, the best result has been obtained by the DenseNet169 model with the highest accuracy of 84% through validation dataset and training dataset compared with DenseNet121 and DenseNet201. The finding is non-trivial, mainly in BCI real-time implementation as the steps of processing has been reduced through the implementation of TL models to extract significant features. Future studies shall attempt on the evaluation of other TL models that could process the features faster compared with current TL models that has been utilized in this research.

References

[1] K. Ganasegeran, M. Fadzly, A. Jamil, and S. Sivasampu, “Discover! Malaysia’s Stroke Care Revolution - Special Edition,” *ResearchGate*, vol. 2, no. 1, pp. 1–32, 2019.

[2] WHO, “Rehabilitation A Call For Action : The Need To Scale Up Rehabilitation,” pp. 1–9, 2015.

[3] D. J. Moritz, P. J. Fox, P. A. Luscombe, and H. C. Kraemer, “Neurological and psychiatric predictors of mortality in patients with Alzheimer disease in California,” *Arch. Neurol.*, vol. 54, no. 7, pp. 878–885, 2019.

[4] B. Artery and R. Artery, “If Stroke Happens ,” 2020.

[5] S. Jaradeh, “Neuromuscular Disorders,” *Wis. Med. J.*, vol. 96, no. 3, p. 44, 2019.

[6] New Scientist, “Eight wonders of the human brain,” *New Sci.*, vol. 242, no. 3235, pp. 34–41, 2019.

[7] J. S. Kumar and P. Bhuvaneswari, “Analysis of electroencephalography (EEG) signals and its categorization - A study,” *Procedia Eng.*, vol. 38, pp. 2525–2536, 2012.

[8] J. J. Shih, D. J. Krusienski, and J. R. Wolpaw, “Brain-computer interfaces in medicine,” *Mayo Clin. Proc.*, vol. 87, no. 3, pp. 268–279, 2012.

[9] D. P. Subha, P. K. Joseph, R. Acharya U, and C. M. Lim, “EEG signal analysis: a survey.,” *J. Med. Syst.*, vol. 34, no. 2, pp. 195–212, 2010.

[10] O. April and P. Obama, “Brain Research through Advancing Innovative Neurotechnologies (BRAIN),” 2015.

[11] F. Domrös, D. Störkle, J. Ilmberger, and B. Kuhlenkötter, “Converging Clinical and Engineering Research on Neurorehabilitation,” *Converging Clin. Eng. Res. Neurorehabilitation*, vol. 1, pp. 409–413, 2013.

[12] A. Abdelhameed and M. Bayoumi, “Semi-Supervised Deep Learning System for Epileptic Seizures Onset Prediction,” *Proc. - 17th IEEE Int. Conf. Mach. Learn. Appl. ICMLA 2018*, pp. 1186–1191, 2019.

[13] P. Coelho, A. Pereira, and M. Salgado, “A Deep Learning Approach for Red Endoscopies,” 2018,

vol. 1, no. June, pp. 553–561.
[14] T. M. Vaughan, "Brain-computer interface technology: A review of the Second International Meeting," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 11, no. 2, pp. 94–109, 2003.
[15] J. S. Lin and C. H. Hsieh, "A Wireless BCI-Controlled Integration System in Smart Living Space for Patients," *Wirel. Pers. Commun.*, vol. 88, no. 2, pp. 395–412, 2016.
[16] Ö. Türk and M. S. Özerdem, "Epilepsy detection by using scalogram based convolutional neural network from eeg signals," *Brain Sci.*, vol. 9, no. 5, 2019.
[17] T. A. M. L. Tobing, Prawito, and S. K. Wijaya, "Classification of right-hand grasp movement based on EMOTIV Epoc+," *AIP Conf. Proc.*, vol. 1862, 2017.
[18] E. Stoelinga, "Exploring the possibilities of the Emotiv Insight : discriminating between left- and right-handed responses Methods Participants," no. 2013, pp. 1–11, 2016.
[19] K. Tsiouris, V. C. Pezoulas, M. Zervakis, S. Konitsiotis, D. D. Koutsouris, and D. I. Fotiadis, "A Long Short-Term Memory deep learning network for the prediction of epileptic seizures using EEG signals," *Comput. Biol. Med.*, vol. 99, no. March, pp. 24–37, 2018.
[20] K. Kato, K. Takahashi, N. Mizuguchi, and J. Ushiba, "Online detection of amplitude modulation of motor-related EEG desynchronization using a lock-in amplifier: Comparison with a fast Fourier transform, a continuous wavelet transform, and an autoregressive algorithm," *J. Neurosci. Methods*, vol. 293, pp. 289–298, 2018.
[21] M. Mustafa, M. Nasir Taib, Z. Hj. Murat, and N. Sulaiman, "Comparison between KNN and ANN Classification in Brain Balancing Application via Spectrogram Image," *J. Comput. Sci. Comput. Math.*, vol. 2, no. 4, pp. 17–22, 2012.
[22] R. Khosrowabadi and A. W. B. A. Rahman, "Classification of EEG correlates on emotion using features from Gaussian mixtures of EEG spectrogram," *Proceeding 3rd Int. Conf. Inf. Commun. Technol. Moslem World ICT Connect. Cult. ICT4M 2010*, pp. E102–E107, 2010.
[23] A. Chronopoulou, C. Baziotis, and A. Potamianos, "An Embarrassingly Simple Approach for Transfer Learning from Pretrained Language Models," pp. 2089–2095, 2019.
[24] B. Amanpour and A. Erfanian, "Classification of brain signals associated with imagination of hand grasping, opening and reaching by means of wavelet-based common spatial pattern and mutual information," *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS*, pp. 2224–2227, 2013.
[25] S. Chengaiyan, A. S. Retnapandian, and K. Anandan, "Identification of vowels in consonant–vowel–consonant words from speech imagery based EEG signals," *Cogn. Neurodyn.*, vol. 14, no. 1, pp. 1–19, 2019.
[26] P. Xie, T. Li, J. Liu, S. Du, X. Yang, and J. Zhang, "Urban flow prediction from spatiotemporal data using machine learning: A survey," *Inf. Fusion*, vol. 59, no. November 2019, pp. 1–12, 2020.
[27] J. Tao and X. Fang, "Toward multi-label sentiment analysis: a transfer learning based approach," *J. Big Data*, vol. 7, no. 1, pp. 1–26, 2020.
[28] S. Deepak and P. M. Ameer, "Brain tumor classification using deep CNN features via transfer learning," *Comput. Biol. Med.*, vol. 111, no. March, p. 103345, 2019.
[29] G. Louppe, "Understanding Random Forests: From Theory to Practice," no. July, 2014.
[30] R. Pal, *Predictive modeling based on random forests*. 2017.
[31] K. Raeisi, M. Mohebbi, M. Khazaei, M. Seraji, and A. Younesi, "Phase-synchrony evaluation of EEG signals for Multiple Sclerosis diagnosis based on bivariate empirical mode decomposition during a visual task," *Comput. Biol. Med.*, vol. 117, no. December 2019, p. 103596, 2019.
[32] M. F. Bari and S. Anowarul Fattah, "Epileptic seizure detection in EEG signals using normalized IMFs in CEEMDAN domain and quadratic discriminant classifier," *Biomed. Signal Process. Control*, vol. 58, p. 101833, 2020.
[33] M. Z. Baig and M. Kavakli, "Classification of User ' s Expertise in Five Levels using EEG and Convolutional Neural Network in Modelling Application," *Expert Syst. Appl.*, vol. 146, p. 113202, 2020.
[34] U. R. Acharya, S. L. Oh, Y. Hagiwara, J. H. Tan, and H. Adeli, "Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signals," *Comput. Biol. Med.*, vol. 100, no. August 2017, pp. 270–278, 2018.
[35] P. Flach, "Performance Evaluation in Machine Learning: The Good, the Bad, the Ugly, and the Way Forward," *Proc. AAAI Conf. Artif. Intell.*, vol. 33, pp. 9808–9814, 2019.
[36] M. Sokolova and G. Lapalme, "A systematic analysis of performance measures for classification tasks," *Inf. Process. Manag.*, vol. 45, no. 4, pp. 427–437, 2009.
[37] S. Vijay Anand and R. Shantha Selvakumari, "Noninvasive method of epileptic detection using DWT and generalized regression neural network," *Soft Comput.*, vol. 23, no. 8, pp. 2645–2653, 2019.