THE CLASSIFICATION OF WINK-BASED EEG SIGNALS BY MEANS OF TRANSFER LEARNING MODELS

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SUPERVISOR'S DECLARATION

I hereby declare that I have checked this thesis and in my opinion, this thesis is adequate in terms of scope and quality for the award of the degree of Master of Science.

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I hereby declare that the work in this thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Universiti Malaysia Pahang or any other institutions.

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ABSTRAK

Strok merupakan salah satu punca kecacatan fizikal yang dominan. Dianggarkan sehingga separuh daripada mangsa strok mangalami kecederaan motor atau kognitif yang agak kronik. Kesan langsung daripada penyakit neurologi ini adalah kesukaran pergerakkan tubuh badan yang terlibat dan menyebabkan kesukaran untuk pesakit strok menjalankan akitiviti kehidupan harian. Isyarat EEG ini merupakan beza upaya antara neuron-neuron di dalam otak ketika sesuatu aktiviti dijalankan oleh manusia. Isyarat ini telah digunakan secara meluas dalam teknologi antara muka otak-komputer seperti kawalan rangka luar (exoskeleton) untuk pesakit strok bagi memudahkan mereka melaksanakan aktiviti harian. Pengekstrakan ciri-ciri penting dari isyarat EEG merupakan suatu yang mencabar, namun dalam pelbagai kepustakaan saintifik telah menunjukkan keberkesanan pengunaan algoritma pembelajaran mendalam (deep learning algorithm) terutamanya algoritma pembelajaran pindahan (Transfer Learning) dalam pelbagai aplikasi. Setakat ini, kajian pengelasan isyarat EEG menggunakan pembelajaran pindahan berserta dengan pembelajaran mesin ini amat terhad. Kebanyakannya tertumpu kepada isyarat EEG berdasarkan aktiviti kenyitan mata. Kajian ini bertujuan untuk menyiasat kaedah pra-pemprosesan yang berbeza, iaitu ‘Fast Fourier Transform’, ‘Short Time Fourier Transform’, ‘Discrete Wavelet Transform’, dan ‘Continuous Wavelet Transform (CWT)’. Kaedah-kaedah pra-pemprosesan ini telah digunakan untuk menukar isyarat digital yang diperolehi daripada sepuluh (4 Perempuan dan 6 Lelaki, berumur diantara 22 hingga 29) subjek kepada imej mengikut algoritma tersendiri. Pelaksanaan algoritma pra-pemprosesan telah menunjukkan pengurangan isu-isu isyarat hingar. Satu kaedah input baru yang menggabungkan masa dan domain frekuensi telah diperkenalkan. Model pembelajaran pindahan yang berbeza telah dieksploitasi untuk mengekstrakkan ciri-ciri penting dari isyarat EEG yang telah ditransformasikan. Ciri-ciri yang diekstrak telah dikelaskan melalui tiga model pembelajaran mesin klasik iaitu ‘Support Vector Machine’, ‘k-Nearest Neighbour (*k*-NN)’, dan ‘Random Forest’ untuk menentukan cara pengelasan yang terbaik untuk isyarat EEG yang berdasarkan mengenyit mata. Hiperparameters bagi model pembelajaran mesin telah ditala melalui teknik pengesahan silang lima kali ganda melalui teknik carian grid. Latihan, pengesahan dan ujian model telah dibahagikan dengan nisbah berstrata masing-masing pada 60:20:20. Keputusan yang diperolehi daripada model yang mengandungi TL-ML ini, dinilai dari segi ketepatan pengelasan dan matriks kekalutan untuk memastikan kebolehgunaan model yang dibangunkan, dilaksanakan dalam sistem antara muka otak-komputer misalnya kawalan rangka luar untuk pergerakan menggenggam. Daripada simulasi, CWT model telah menghasilkan transformasi isyarat yang lebih baik di kalangan algoritma yang telah diproseskan. Di samping itu, daripada kalangan lapan belas model TL yang dinilai berdasarkan transformasi CWT, lapan model dapat mengekstrak ciri-ciri isyarat yang penting, iaitu VGG16, VGG19, ResNet152, Inception V3, Inception ResNet V2, MobileNetV2, DenseNet 169 and NasNetMobile. Dalam pemerhatian penyelidik, didapati model *k*-NN yang telah dioptimumkan berbanding model-model yang disebut diatas boleh mencapai ketepatan pengelasan 100% melalui latihan, pengesahan, dan data ujian. Walau bagaimanapun, apabila menjalankan ujian keteguhan ke atas data baru, ia menunjukkan bahawa model ‘NasNetMobile’ adalah yang terbaik. Kesimpulanya, model yang mengandungi CWT-NasNetMobile-*k*-NN yang dicadangkan adalah sesuai untuk melaksanakan pengelasan isyarat EEG yang berasaskan kenyitan mata dalam sistem antara muka otak-komputer.

ABSTRACT

Stroke is one of the dominant causes of impairment. An estimation of half post-stroke survivors suffer from a severe motor or cognitive deterioration, that affects the functionality of the affected parts of the body, which in turn, prevents the patients from carrying out Activities of Daily Living (ADL). EEG signals which contains information on the activities carried out by a human that is widely used in many applications of BCI technologies which offers a means of controlling exoskeletons or automated orthosis to facilitate their ADL. Although motor imagery signals have been used in assisting the hand grasping motion amongst others motions, nonetheless, such signals are often difficult to be generated. It is non-trivial to note that EEG-based signals for instance, winking could mitigate the aforesaid issue. Nevertheless, extracting and attaining significant features from EEG signals are also somewhat challenging. The utilization of deep learning, particularly Transfer Learning (TL), have been demonstrated in the literature to be able to provide seamless extraction of such signals in a myriad of various applications. Hitherto, limited studies have investigated the classification of wink-based EEG signals through TL accompanied by classical Machine Learning (ML) pipelines. This study aimed to explore the performance of different pre-processing methods, namely Fast Fourier Transform, Short-Time Fourier Transform, Discrete Wavelet Transform, and Continuous Wavelet Transform (CWT) that could allow TL models to extract features from the images generated and classify through selected classical ML algorithms. These pre-processing methods were utilized to convert the digital signals into respective images of all the right and left winking EEG signals along with no winking signals that were collected from ten (6 males and 4 females, aged between 22 and 29) subjects. The implementation of pre-processing algorithms has been demonstrated to be able to mitigate the signal noises that arises from the winking signals without the need for the use signal filtering algorithms. A new form of input which consists of scalogram and spectrogram images that represents both time and frequency domains, are then introduced in the classification of wink-based EEG signals. Different TL models were exploited to extract features from the transformed EEG signals. The features extracted were then classified through three classical ML models, namely Support Vector Machine, k-Nearest Neighbour (*k*-NN) and Random Forest to determine the best pipeline for wink-based EEG signals. The hyperparameters of the ML models were tuned through a 5-fold cross-validation technique via an exhaustive grid search approach. The training, validation and testing of the models were split with a stratified ratio of 60:20:20, respectively. The results obtained from the TL-ML pipelines were evaluated in terms of classification accuracy, Precision, Recall, F1-Score and confusion matrix. It was demonstrated from the simulation investigation that the CWT model could yield a better signal transformation amongst the preprocessing algorithms. In addition, amongst the eighteen TL models evaluated based on the CWT transformation, fourteen was found to be able to extract the features reasonable, i.e., VGG16, VGG19, ResNet101, ResNet101 V2, ResNet152, ResNet152 V2, Inception V3, Inception ResNet V2, Xception, MobileNetV2, DenseNet 121, DenseNet 169, NasNetMobile and NasNetLarge. Whilst it was observed that the optimized *k*-NN model based on the aforesaid pipeline could achieve a classification accuracy of 100% for the training, validation, and test data. Nonetheless, upon carrying out a robustness test on new data, it was demonstrated that the CWT-NasNetMobile-*k*-NN pipeline yielded the best performance. Therefore, it could be concluded that the proposed CWT-NasNetMobile-*k*-NN pipeline is suitable to be adopted to classify-wink-based EEG signals for BCI applications,for instance a grasping exoskeleton.

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h_i and h_j	Samples in RBF kernel
D_i	A class in a node
N'	The shifting step of the window
$R_{xx}(.)$	Serial correlation function
$S_{xx}(w)$	Power Spectral Density (PSD)
$X_w(a,b)$	The coefficients of the wavelets
a_i and a_j	Input for linear kernel (two types of samples)
b_i and b_j	Features for the input space in Polynomial kernel
m_1	Taxicab distance (Manhattan Distance)
ψ^*	The conjugate of the basic wavelet function
a	Is the approximate scale to frequency conversion for specified wavelet
A and B	Vectors of Minkowski distance
b	The position parameter
k	The shifting parameter that dominates the threshold of the calculation in sigmoid kernel
m	Vector space in Manhattan distance
n	Cartesian coordinate in Manhattan Distance
N	The length of the window segments
q	Interger between A and B
x(t)	Deterministic signal in time domain
X(w)	Fourier Transform of the signal x(t)
z and y	Cumulative length of each line section (Euclidean distance)
C	Regularization Parameter in Support Vector Machine (SVM) parameter
Hz	Hertz
$N(D_i)$	The class probability
$S(m,k)$	m-index time-frequency spectrogram
X and Y	Two attribute vectors in Cosine Distance
$Z(m,k)$	Magnitude of the m-index time frequency spectrogram
c	The optional constant in linear kernel

d	Degree of Polynomial Kernel
e	Constant value in polynomial kernel which should be more than zero
$w(n)$	Window method of an N-point sequence
x	The scaling parameter of the input vectors in Sigmoid kernel
$z(t)$	Equivalent time signal
γ	Gamma value in SVM parameter
μV	Micro Volt
σ	Free parameter in RBF kernel

LIST OF ABBREVIATIONS

AC	Alternating Current
ADL	Activities of Daily Living
BCI	Brain Computer Interfaces
CA	Classification Accuracy
CM	Confusion Matrix
CMS	Common Mode Sense
CNN	Convolutional Neural Network
CWT	Continuous Wavelet Transform
DC	Direct Current
DFT	Discrete Fourier Transform
DRL	Driven Right Leg
DWT	Discrete Wavelet Transform
EEG	Electroencephalogram
EI	Emotiv Insight
EI	Emotive Insight
EOG	Electrooculography
FFT	Fast Fourier Transform
FN	False Negative
FP	False Positive
k-NN	k-Nearest Neighbour
k-value	Number of neighbour parameter
LCD	Liquid Crystal Display
LSB	Least Significant Bit
LW	Left Winking
ML	Machine Learning
mRS	modified Ranking Scale
n_estimators	Number of trees that the model frame up before evaluation
NW	No Winking
OVAT	One-value-at-a time
Poly	Polynomial
PPV	Positive Predictive Value

PSD	Power Spectral Density
RBF	Radial Basis Function
RF	Random Forest
RW	Right Winking
SOP	Standard Operating Procedure
STFT	Short Time Fourier Transform
SVM	Support Vector Machine
TL	Transfer Learning
TN	True Negatives
TP	True Positives
WHO	World Health Organization
WT	Wavelet Transform

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