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Wavelet-based Hybrid Learning Framework for Motor Imagery Classification

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Abstract
Due to their vital applications in many real-world situations, researchers are still presenting bunches of methods for better analysis of motor imagery (MI) electroencephalograph (EEG) signals. However, in general, EEG signals are complex because of their nonstationary and high-dimensionality properties. Therefore, high consideration needs to be taken in both feature extraction and classification. In this paper, several hybrid classification models are built and their performance is compared. Three famous wavelet mother functions are used for generating scalograms from the raw signals. The scalograms are used for transfer learning of the well-known VGG-16 deep network. Then, one of six classifiers is used to determine the class of the input signal. The performance of different combinations of mother functions and classifiers are compared on two MI EEG datasets. Several evaluation metrics show that a model of VGG-16 feature extractor with a neural network classifier using the Amor mother wavelet function has outperformed the results of state-of-the-art studies.

KEYWORDS: Brain-Computer Interface, Deep Learning, Motor Imagery, Transfer Learning, Wavelet Transformation.

I. Introduction

Technology for human-computer interaction has evolved quickly in recent years, and the bioelectricity of the human body is being developed as an interactive medium. A brain-computer interface (BCI) system uses brain impulses to operate auxiliary equipment as a novel method of human-computer interaction [1]. In a BCI system, a direct link between the brain and a computer is established, bypassing the peripheral nervous system and providing a communication channel. ALS (Amyotrophic lateral sclerosis), cerebral palsy, and motor neuron disease (MND) are all examples of brain illnesses that can benefit from BCI technology (MND) [2]. An EEG is the most preferred physiological sensor for developing a BCI system since it meets both convenience criteria (i.e., non-intrusiveness and simplicity) as well as efficacy criteria (such as accuracy) (i.e., sensitivity, efficiency, and compatibility) [3]. P300 evoked potentials, steady-state visual evoked potentials (SSVEP), and Motor imagery (MI) are among the most prominent EEG signal analysis disciplines [1]. Only MI relies on spontaneous potential and does not require any external stimulation. Researchers have employed MI signals to assist handicapped people in managing equipment like wheelchairs and even self-driving cars [4]. Imagine moving your body part without really moving that body part, which is known as MI [5]. EEG signals are generated by both imagined and actual human movement. In motor imaging, the EEG signals generated exhibit event-related synchronization (ERS) and event-related desynchronization (ERD) features [6]. There are four lobes in each of the human brain hemispheres, each serving a distinct purpose. Fissures divide the lobes of the ear (sulcus). In the BCI system, the primary somatic sensory cortex (parietal lobe) and the primary motor cortex (temporal lobe) are the most critical areas [7]. Mu and beta rhythms in the sensorimotor part of one's hemisphere drop or increase as one imagines or performs the movement of a unilateral limb. Desynchronization caused by an event (ERD) and synchronisation caused by an event (ERS) are two different concepts [7].

Fundamentally, MI-based BCI pattern recognition systems require three essential processes, namely preprocessing of the EEG signal, feature extraction, and classification [1]. Essentially, another crucial process in the MI EEG pattern recognition model is the process of feature extraction. Practically, extracted features are intended to minimize the cost of data processing by recognizing the most relevant feature components embedded in the signal.

In this respect, the feature extraction process can be conducted in multiple signal processing domains, such as spatial domain, time domain, frequency domain, and time-frequency domain. Particularly, time-frequency features of MI EEG signals are widely used for classification in BCI applications, whereas it describes the density and intensity of energy of signal at a different time and frequency by designing a joint function of time and frequency [1]. Principally, EEG signal analysis in the time-frequency domain based on wavelet transform (WT) das proved their ability and usefulness in handling brain signal characteristics compared to other methods such as short-time Fourier transform (STFT), autoregressive model (ARM), and wavelet transform (WT) [8]. To date, great attention is given to the WT in the field of biomedical signal processing because of its efficiency in the diagnostic as well as in the pattern recognition [1].

Deep neural networks (DNNs) have recently demonstrated impressive categorization capabilities in a variety of applications, including computer vision, video processing, and speech recognition. Several academics were inspired by its enormous success to investigate how deep neural networks may be used to categorize EEG signals [9, 10]. Researchers have begun using deep learning in their BCI applications, including seizure detection, memory retrieval, and MI categorization [11]. The convolution neural network (CNN) has demonstrated that it is capable of extracting spatial and temporal characteristics from magnetic induction (MI) data. It has been shown that CNN can extract excellent features using both shallow and deep models, indicating that significant features may be retrieved at different levels [4].

However, one of the most significant challenges in the categorization of MI EEG characteristics using deep learning algorithms is the limited amount of data available due to the exhaustion of patients throughout the experiments [7]. There are also significant individual variations between various subjects, making it hard to directly utilize the labeled data from other subjects to train the classifier that would be used to identify the target individuals [12]. Meanwhile, the collection of EEG data is extremely costly, and a sufficient quantity of labeled samples is difficult to come by [13]. When it comes to combining data from domains with different distributions, transfer learning has emerged as a viable approach. Incorporated within transfer learning are methods that are designed to transfer representations and information from one domain to another [14]. In other words, the approach enables researchers to easily integrate fresh datasets into a machine learning model that has already been trained. Having this functionality can be especially useful in a BCI system since the amount of data supplied is frequently insufficient to ensure the appropriate training of a machine learning model [15]. In the BCI studies, it was discovered that the CNN-based subject-transfer technique outperformed the others. Subject-transfer strategies are based on the idea that the typical patterns of the target subject and other subjects may be comparable when doing the same activity [16].

It is critical to select the ideal mother wavelet along the course of using WT with deep transfer learning. The selection of a mother wavelet (MWT) function, on the other hand, has been reported in the literature as an important step and component of wavelet analysis to demonstrate the advantages of WT in denoising, component separation, coefficient reconstruction, and feature extraction from signals in the time and frequency domains [17]. The need for this phase arises from the fact that no unique MWT basis functions have yet been identified that cater to all EEG channels.

Specifically, the research proposes an approach for feature extraction and classification that is based on a continuous wavelet transform (CWT) in conjunction with deep learning-based transfer for feature extraction and artificial neural network (ANN) for classification.

The following is the structure of the reminder for this paper: WTNN development, evaluation, and validation were all carried out under a methodological framework defined in Section 2. Sections 3 and 4, which summarise the findings and commentary for the experimental component, respectively, are based on two separate datasets, namely the BCI Competition dataset IV/2b and the Emotive EPOC dataset, and are divided into two sections. After that, the final section of this study displays the findings of this research.

II. Literature Review

Al-Qazzaz reported in [18] that even a 0.1% intensification in the classification accuracy in medical research fields is considered vital due to the high complexity of their signals. Therefore, many methods are proposed to attain the highest classification accuracy.

Xu et. al. [19] used a transference CNN framework based on VGG-16 and time-frequency spectrum images generated by STFT for analyzing MI EEG signals. They obtained 71.2% of BCI competition classification accuracy for the IV 2b dataset. Using a continuous wavelet transform (CWT) filter bank to classify four MI tasks (left hand, right hand, feet, and tongue).

Mahamune and Laskar [20] proposed a framework for developing two-dimensional (2D) images for CNNs that uses a continuous wavelet transform (CWT) filter bank to classify four MI tasks. On the BCI competition IV 2a dataset, they achieved an accuracy of 71.25 percent in classification accuracy. Using a common spatial pattern (CSP) and filtering in conjunction with the empirical mode decomposition (EMD).

Alvarez-Meza et al. [21] were able to distinguish the mu and beta rhythms from one another. The support vector machine (SVM) classifier was utilized by the researchers. They attained classification accuracy of 92.86 percent on the BCIC IV-I dataset and 72.30 percent on the BCIC IV 2b dataset, respectively, on the two datasets.

Wang et. al. [22] proposed a method based on CSP as preprocessing while feature extraction was done using autoregressive and log-variance; the Kullback-Leibler divergence was for feature selection and time segment selection. Th classification is achieved using the linear discriminate analysis technique. They achieved a classification accuracy of 81.99% and 77.22% on BCIC IV 2a and BCIC IV 2b datasets respectively.

Xu et. al. [23] proposed a method involving extracting features based on Hjorth parameter, the power spectrum estimation, and time-frequency energy. Then sparse representation was used to acquire lower-dimensional informative features while keeping the discriminative ability among the different patterns. They obtained 79% of classification accuracy on BCIC IV 2b. Oh et. al. [24] used Hjorth parameter and Fisher ratio to find the dominant frequency bands and the timing in training EEG signals and 79.1% of classification accuracy was achieved on BCIC IV 2b.

Bagh and Reddy [25] used the Hilbert transform (HT) for the recognition of Event-related potentials, and the SVM for decoding the MI signals. They obtained 86.11% and 82.50% of classification accuracy on BCIC III 3a and BCIC IV 2b respectively.

Zhu et. al. [26] The multi-channel input is encoded using a separated channel convolutional network, and the encoded features are concatenated and fed into a recognition network, which performs the final MI task recognition. They obtained 83% of classification accuracy on BCIC IV 2b.

Dai et. al. [27] proposed a segmentation data augmentation method for MI EEG signals and used the new trails for training a CNN. They obtained 91.57% and 83% of classification accuracy on BCIC IV 2a and BCIC IV 2b respectively.

Kim et. al. [28] proposed a method that rely on the power spectral density (PSD) to find the noon-stationarity feature of each couple of EEG channels by calculating a matrix for that. Such that, they exploited the time, frequency, and spatial characteristics of the time-series signals. They obtained 89.36% of classification accuracy on BCIC IV 2a for only two classes classification.

Sun et. al. [29] used an EOG channel for retaining the potential related to MI tasks with the combination of Hjorth algorithm to train their model. They obtained 76.45% and 0.79% of classification accuracy on BCIC IV 2a and BCIC IV 2b respectively.

Kant et. al. [30] combined the continuous wavelet transform (CWT) with deep learning-based transfer learning and compared this method to different well-known deep CNNs using the BCIC III 3a dataset. They obtained 95.71% as the best classification accuracy that is retained by the VGG-19. Although there are several studies tried to improve the accuracy of classification, the results of the reviewed studies show that their still an area for enhancement.

III. Methodology

The methodological framework of the WTNN for the two-class MI EEG classification problem is presented in Fig. 1. This framework describes the whole process of pattern recognition starting from preparing the training samples and ending with the performance evaluation stage. The following subsections give more details concerning the methodology of this research.

A. MI EEG Datasets

A minimum number of channels is normally preferred by developers in designing BCI-based systems such that they can be easily employed with minimum cost for real-time applications [31]. Therefore, two MI EEG datasets recorded by 3 channels are chosen in this study. The two datasets are from the BCI competition datasets recorded at Graz University. More details regarding the two datasets are given in the following subsections. The datasets consist of two parts, namely the training part and the validation part. As such, it was used in developing and validating the WTNN to deal with the complexity of the nine subjects' specific brain signals, such as inter and intra-subject differences. Given the lack of a large dataset to develop, evaluate, and validate a WTNN, the datasets of all the nine subjects were combined (union) to form a large dataset for all the trials involving different brain complexities.

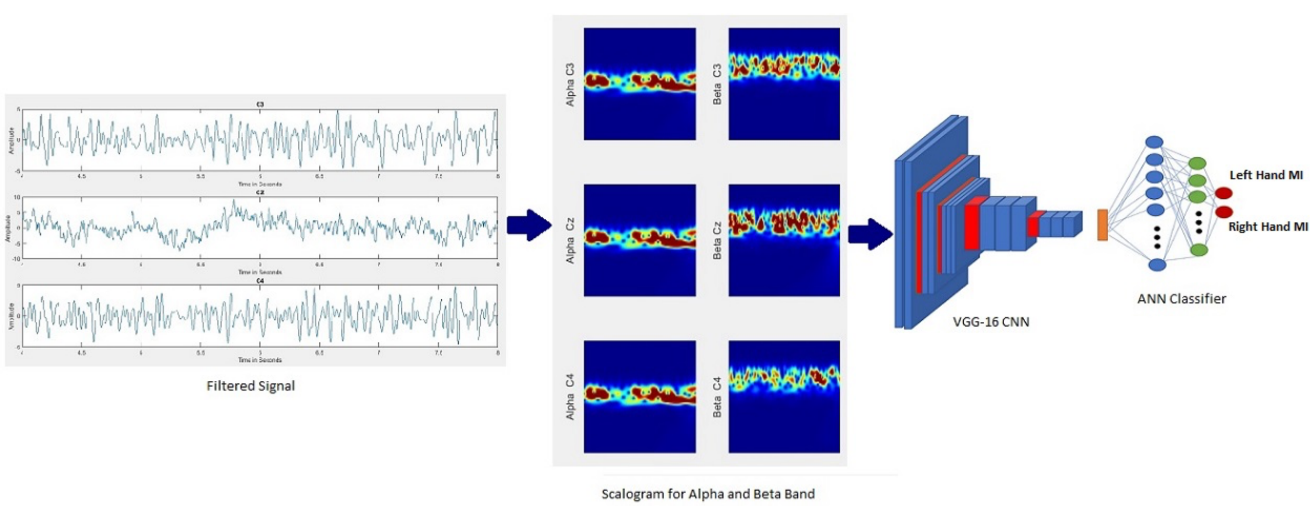
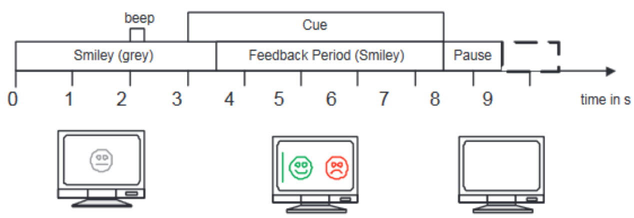


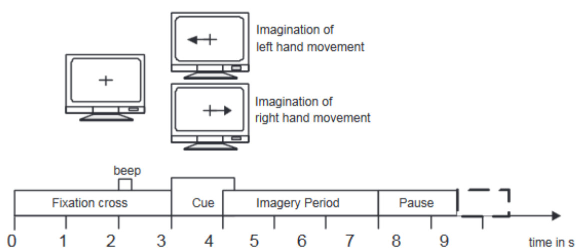
Fig. 1: Methodological Framework for WTNN model

- *BCIC IV 2b dataset*

In this dataset, three EEG channels namely C3, Cz, and C4 were used to acquire the signals of two motor imagery tasks (left hand and right hand). The dataset was collected from nine subjects at a 250 Hz sampling frequency. EEG data from 160 trials were collected while a subject watching a flat-screen and sitting in an armchair. Two types of recording sessions were conducted, namely training without feedback and evaluation with smiley feedback. During the first two sessions, subjects were given a short warning tone to do four seconds of a required motor imagery movement based on a pointing arrow presented on a blank screen. However, during the other three sessions, subjects were instructed to move grey smiley feedback centered on the monitor into either the right or left direction after they are given a short warning beep. The smiley feedback was presented in four seconds and its color changes to red when it moved in the wrong direction and green when it moved in the right direction. Fig. 2 shows the timing scheme of the two types of sessions.



(a)



(b)

Fig. 2: Trials recording time scheme of BCIC IV 2b dataset (a) without feedback, (b) with smiley feedback.

- *BCIC II dataset*

This dataset was recorded from a normal subject (female, 25y). The experiment consisted of 280 trials of 9 seconds total duration for each trial with a 128 Hz sampling frequency. The subject was quiet for the first 2s, at t=2s an acoustic stimulus indicating the beginning of the trial and across '+' were displayed for 1s. Then at t=3s, an arrow (left or right) was presented as a cue. Simultaneously, the subject was requested to perform the required motor imagery task (left hand or right hand). The EEG data was filtered between 0.5 and 30 Hz. The imaginary task was to move a block based on the given cue in the left or right direction. The used three EEG channels were C3, Cz, and C4. Each session contains 40 trials, half of them are for left-hand and half for right-hand which are placed randomly. Seven sessions of such 40 trials have been recorded with their labels [30]. Fig. 3 shows the timing scheme of the recording technique.

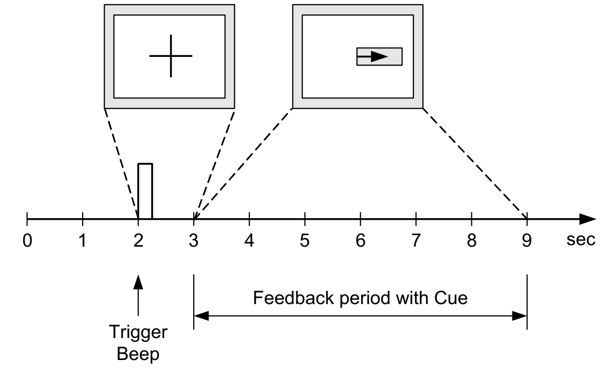


Fig. 3: Trials recording time scheme of BCIC II dataset.

B. Preprocessing

Inevitably, the EEG-MI signal is contaminated by noise from various sources, such as body movements, eye blink, facial muscle movements as well as artifacts from the surrounding environment, such as electromagnetic fields generated by electrical devices [1]. Since the framework relies on deep learning, the least preprocessing is used. Frequency filtering is carried out for enhancing the signal-to-noise ratio of the raw brainwaves and to enhance relevant information of the signals. Specifically, the fourth-order Butterworth filter is applied with the range (8-30 Hz) given that the MI EEG signals rely on the alpha (8-13 Hz) and beta (14-30 Hz) rhythms.

C. Time-Frequency Analysis

The time-frequency domain is a hybrid representation of a time-series signal. In principle, this representation considers the signal properties in both temporal and frequency domains. This representation yields images that highlight the contained frequencies in the time-series signal with the time slot those frequencies have been occurred. Various methods of time-frequency analysis exist such as autoregressive model (ARM), short-time Fourier transform (STFT), wavelet transform (WT), and discrete wavelet transform (DWT). The DWT method has been proven to be more useful in characterizing non-stationary signals effectively. Hence, DWT is adopted in this study for representing the MI EEG signals in 2D images called scalograms.

DWT relies upon dilating and translating a particular function, called a mother wavelet, for representing a signal as a linear combination of a set of wavelet functions. The mother wavelet gives rise to these wavelets as a part of resulting functions through shifting (dilation) and stretching (translation) operations along the time axis, respectively. To date, great attention is given to the WT in the field of biomedical signal processing because of its efficiency in the diagnostic as well as in the pattern recognition [32]. WT is classified into two types; namely continuous wavelet transform (CWT) and discrete wavelet transform (DWT):

$$CWT(a,b) = \int_{-\infty}^{+\infty} x(t)\psi_{a,b}^{*}(t)dt \tag{1}$$

whereas $x(t)$ stands for the time-series signal, a stands for dilation, and b represents the translation factor. The $\psi_{a,b}(t)$ represents the complex conjugate and can be calculated by

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right) \tag{2}$$

where $\psi(t)$ is the wavelet. The major weakness of CWT is that both dilation and translation parameters change continuously. Hence, the wavelet's coefficients for all available scales after calculation require numerous efforts but yields inconsequential information [32]. The wavelet transform method can be considered as a mathematical microscope that splits up a signal into a bunch of signals. In such a method, the same signal corresponding to different frequency bands can be represented to provide frequency bands at appropriate time intervals. Three types of mother wavelets namely Morlet, Bump, and Amor were used in this study

D. Deep Feature Extraction and Classification

The classification problem of EEG signals requires high dimensional features for representing the latent features of the brain signal. Since the classification method plays a major role and has a direct impact on the discrimination between two MI EEG mental commands, therefore, the selection of an appropriate classifier is crucial. The classical machine learning methods need hand-crafted features to perform classification. Deep CNN (DCNN), on the other hand, performs classification by extracting features directly from the raw data [33].

CNN depends on the convolution process in extracting dominant features by adopting several kernels (also known as filters). Small kernels are moved horizontally and vertically along the input sample to capture important features which will be translated as coefficients in those kernels. However, deep learning requires a lot of time and input samples to train big-scale networks. Therefore, transfer learning is adopted to tackle that problem [33]. Transfer learning means the use of an already-trained network in solving another classification problem by re-train a few numbers of its last layers. This saves a lot of time for training and requires fewer training samples than training the network from scratch. In this regard, VGG-16 [33] is a famous CNN model with 16 convolution layers proposed by Oxford Visual Geometry Group in 2014 and it has achieved a outstanding performance in numerous image processing tasks. In this study, the VGG-16 model is used for the MI EEG classification problem. The generated scalograms are used for training the network.

E. WTNN Evaluation Metrics

The performance of the proposed WTNN system has been evaluated using seven metrics namely accuracy, precision, sensitivity, specificity, F1 score, LogLoss, and AUC. TABLE I gives the mathematical equations for each of the metrics with a brief description of each of them [34]. In the table TPL: true positive, TN: true negative, FP: false positive, and TN: true negative.

The Receiver Operating Characteristics (ROC) curve is also used for measuring the performance of the models. The curve is used for checking the performance of the classification model at various threshold settings by distinguishing between classes (i.e., a degree of separability).

To evaluate how well a model will perform on unseen MI EEG inputs, k-fold cross-validation was used in this study. In k-fold cross-validation, the data is divided into k subsets, in which k-1 subsets are used for training the model and the residual subset is used for testing the model. This process is repeated for k times (folds) until all the subsets are used as validation data. The results obtained from the k-folds can be averaged to determine the accuracy of estimation. This study used the 10-fold cross validation for the training

TABLE I
THE USED EVALUATION METRICS

Evaluation metric	Mathematical equation	Explanation
Classification accuracy	$CA = \frac{TP+TN}{TP+FP+FN+TN}$	The ratio of the number of correctly classified samples to the total number of the same class input samples
Precision	$Precision = \frac{TP}{TP+FP}$	The number of correctly classified samples among all the classified samples. It tests the classifier's ability to reject irrelevant subjects.
Recall (Sensitivity)	$Recall = \frac{TP}{TP+FN}$	The number of correctly classified samples from all the positive representations.
F1-score	$F1\text{-score} = \frac{2*TP}{2*TP+FP+FN}$	The F1 score can be described as a weighted average of precision and recall, where an F1 score achieves its best value at 1 and the worst value at 0.
Specificity	$Specificity = \frac{TN}{TN+FP}$	Assesses a model's ability to detect true negatives of each category.
Log Loss	$\text{LogLoss} = -\frac{1}{n}\sum_{i=1}^{n}[y_i\log_e(\hat{y}_i) + (1-y_i)\log_e(1-\hat{y}_i)]$ n: number of samples $\hat{y}_i$: predicted probability per label	Log loss is the crucial classification metric based on probabilities. It defines the probability outputs of a classifier instead of its discrete predictions.

IV. Results and Discussion

It was mentioned that this study uses CWT to transform the given MI EEG signals into scalograms (time-frequency images). Different mother wavelet functions produce different time-frequency characteristics. To examine those differences, three types of mother wavelets namely Morlet, Bump, and Amor were used in this study.

Also, the hybrid feature extraction and classification model has been achieved by using the VGG-16 as a features extractor with one classifier. Six classification algorithms have been examined namely neural network (NN), K-nearest neighbors (KNN), Naïve Bayes (NB), logistic regression (LR), SVM, and decision tree (DT).

The six classifiers are experimented with each of the mother wavelet functions to find the best hybrid model over the combined subject dataset of (BCI Competition dataset 2b , the training part). The results of this experiment are presented as confusion matrices in Fig. 4. A confusion matrix is presented for each classifier and mother wavelet function. Fig. 5 shows the region of convergence (ROC) for each one can see that NN based hybrid model outperformed the performance of other classification methods with the three mother wavelet functions.

It can be noticed that CNN+NN has achieved the best results in comparison to the other experimented hybrid models. The confusion matrix shows 100% classification accuracy with Amor and Morlet wavelet mother functions. For this optimal model, the training time, testing time, and log loss are computed for the three mother functions. As shown in Fig. 6 and overall, the WTNN model with Amor mother functions has delivered the best classification results.

The second experiment is depicted for evaluating the proposed model with another different MI EEG dataset which is (dataset II training part, but for individual subject) . This helps overcome the inter-subject classification problem. To evaluate the optimal model (the WTNN) over different brain signal complexities to overcome the problem of inter-subjects, the model was tested in experiment-2 with another dataset (dataset II evaluation part, individual subjects) that consists of nine subjects. The result showed that the developed model attained 99% of mean accuracy over the nine subjects as presented in TABLE II. Additionally, to evaluate the performance of the WTNN in the ability to overcome intra- subjects' brain signal challenges of sessions (in this study we consider the problem of with feedback and without feedback recording protocols of two sessions). The result showed that the WTNN model attained 99% of mean accuracy over the nine subjects as presented in TABLE III. Comparing the result of this study with academic literature over dataset-I and dataset-II, it is clear that our WTNN model outperformed the accuracy of the literature as presented in TABLE IV and TABLE IV. This comparative result appraises the efficiency of the proposed WTNN model due to the capability of VGG-16 and Amor wavelet in extracting MI signal features. And also, the efficiency of the hybrid model in decoding the right and left commands. This model will contribute to the BCI community by facilitating the deployment of the proposed framework model in MI-based BCI applications.

V. Conclusion

Deep learning and wavelet transformation are useful techniques for dealing with the high-dimensional and nonstationary MI EEG signals. This paper studied the use of deep learning, three different wavelet mother functions, and six different classifiers for the analysis of MI EEG signals. The performance of different combinations of mother functions and classifiers are compared on two MI EEG datasets. Several evaluation metrics show that a model of VGG-16 feature extractor with a neural network classifier using the Amor mother wavelet function has outperformed the results of state-of-the-art studies by achieving 99% of classification accuracy on dataset-II and 100% accuracy on dataset I. This result will facilitate the deployment of an accurate model based on our technique to help the community of the BCI users.

Conflict of Interest

The authors have no conflict of relevant interest to this article.

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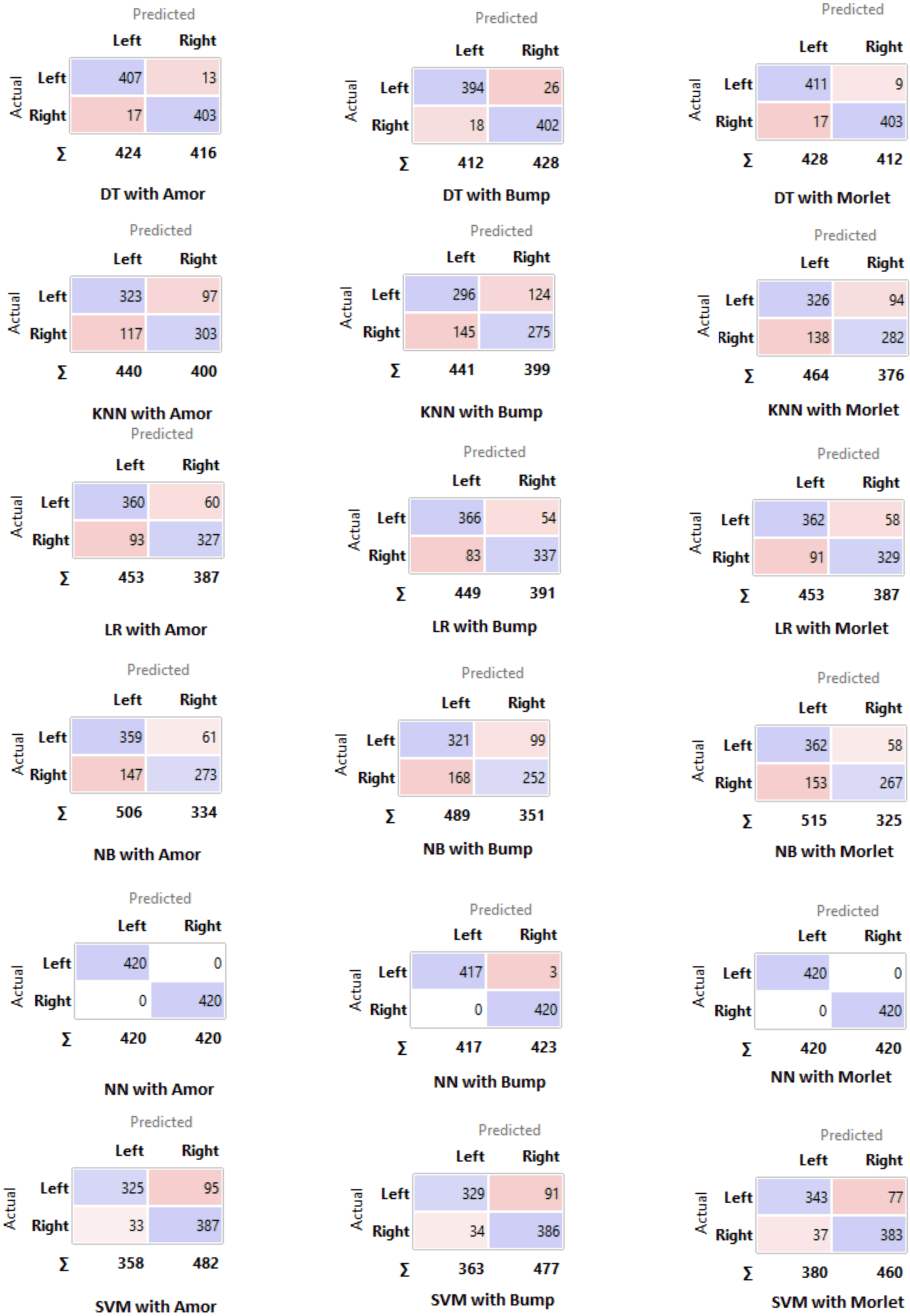
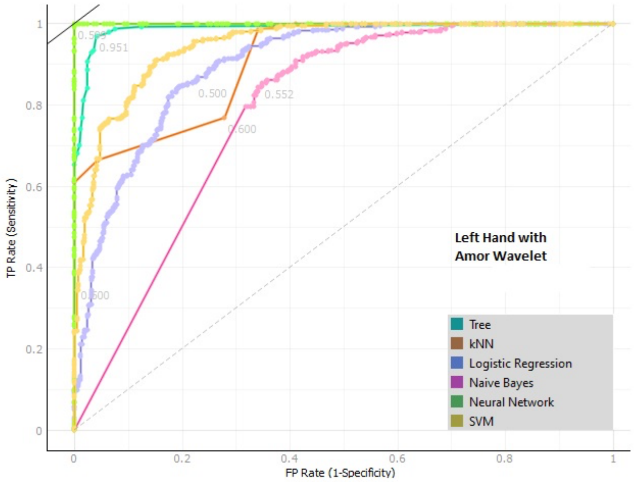


Fig. 4: Confusion matrices of the different hybrid models and different wavelet mother functions.



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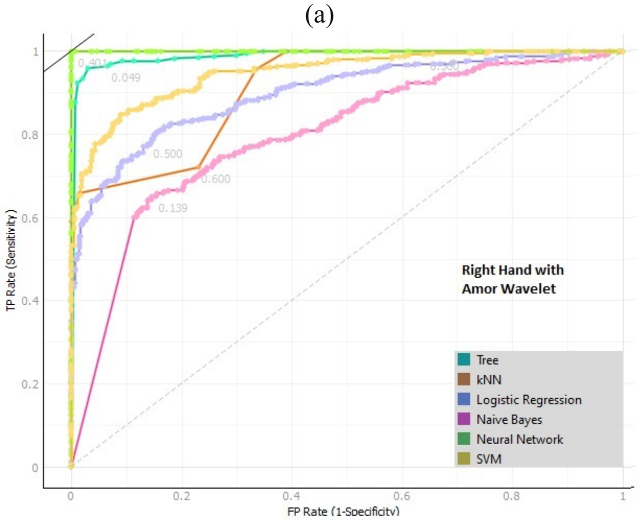

(b)

Fig. 5: ROC (a) for left hand and (b) for right hand.

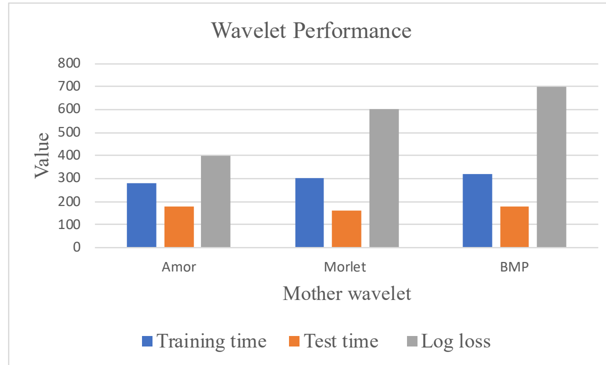

Fig. 6: Training time. test time, log loss for the optimal hybrid model, and different wavelet mother functions.

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TABLE II
WTNN EVALUATION OVER DATASET-II (TRAINING PART)

Subjects	Performance Metrics								
	Training Time	**Testing Time**	**AUC**	**CA**	**F1**	**Precision**	**Recall**	**Logloss**	**Specificity**
S1	301.676	16.456	1.00	0.997	0.997	0.997	0.997	0.014	0.997
S2	322.176	24.112	1.00	1.00	1.00	1.00	1.00	0.004	1.00
S3	299.950	16.285	1.00	0.997	0.997	0.997	0.997	0.006	0.997
S4	294.909	17.193	0.994	0.997	0.997	0.997	0.997	0.035	0.997
S5	292.311	17.040	0.996	0.994	0.994	0.994	0.994	0.038	0.994
S6	310.226	15.267	1.00	0.997	0.997	0.997	0.997	0.008	0.997
S7	305.679	16.797	1.00	0.997	0.997	0.997	0.997	0.006	0.997
S8	335.509	17.225	1.00	0.997	0.997	0.997	0.997	0.014	0.997
S9	293.354	16.175	0.994	0.997	0.997	0.997	0.997	0.031	0.997
Mean	306.1989	17.39444	0.998222	0.997	0.997	0.997	0.997	0.017333	0.997

TABLE III
WTNN EVALUATION OVER DATASET-II (EVALUATION PART)

Subjects	Performance Metrics								
	Training Time	**Testing Time**	**AUC**	**CA**	**F1**	**Precision**	**Recall**	**Logloss**	**Specificity**
S1	381.68	17.501	0.999	0.997	0.997	0.997	0.997	0.020	0.997
S2	293.11	15.572	1.00	0.997	0.997	0.997	0.997	0.008	0.997
S3	317.75	18.519	0.992	0.994	0.994	0.994	0.994	0.129	0.994
S4	83.14	4.244	1.00	1.00	1.00	1.00	1.00	0.006	1.00
S5	118.32	4.601	1.00	0.998	0.998	0.998	0.998	0.014	0.998
S6	104.40	6.487	1.00	0.997	0.997	0.997	0.997	0.011	0.997
S7	128.03	7.797	1.00	0.994	0.994	0.994	0.994	0.011	0.994
S8	123.33	6.893	0.990	0.994	0.994	0.994	0.994	0.048	0.994
S9	117.84	6.605	1.00	0.994	0.994	0.994	0.994	0.015	0.994
Mean	185.28	9.802	0.998	0.99	0.996	0.996	0.996	0.029	0.996

TABLE IV
RESULTS COMPARISON WITH STATE-OF-THE-ART STUDIES RELATED TO DATASET-I

Year	Study	Method	Accuracy
2015	[35]	LDA + based wrapper SFS	90%
2016	[36]	STFT with KNN	83.57%
2016	[37]	WT + SE using SVM and KNN	86.4%
2016	[38]	MEMD + STFT with KNN	90.71%
2017	[39]	Fuzzified Adaptation with SVM	81.48%
2019	[40]	Genetic Algorithm with FKNN	84%
2019	[41]	STFT with CNN	89.73%
2019	[42]	CWT with 1D CNN	92.9%
2020	[30]	WPT + CWT with CNN	95.71%
2021	[43]	WTTD + CWT with CNN	96.43%
2022	This Study	CWT (Amor and Morlet) + VGG-16 + NN	100%

TABLE V
RESULTS COMPARISON WITH STATE-OF-THE-ART STUDIES RELATED TO DATASET-II

Year	Study	Method	Accuracy
2014	[24]	Hjorth parameter + LDA	79.1%
2015	[21]	CSP + EMD	72.30%
2018	[22]	CSP + autoregressive model	77%
2018	[28]	WDPSD	89.36%
2018	[29]	A normalization model with one contralateral EOG channel	96.86%
2019	[26]	a separated channel convolutional network	83%
2019	[19]	STFT + VGG16	71.2%
2020	[23]	multi-domain features	79%
2020	[27]	CNN with hybrid convolution scale	87.6%
2020	[25]	Hilbert transform (HT)-SVM	82.50%
2020	[30]	CWT + VGG19	97.06%
2021	[20]	CWT + CNN	71.25
2022	This Study	CWT (Amor and Morlet) + VGG-16 + NN	99%

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