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Artificial Intelligence in Brain Computer Interface

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***Abstract*— A brain-computer interface (BCI) is a connection path among brain and an external device. Motor imagery (MI) is proven to be a useful cognitive technique for enhancing motor skills as well as for movement disorder rehabilitation therapy. It is known that the efficiency of MI training can be enhanced by using BCI approach, which provides real-time feedback on the mental attempts of the subject. Artificial intelligence (AI) methods play a key role in detecting changes in brain signals and converting them into appropriate control signals. In this paper, we focus on brain signals that have been obtained from the scalp to control assistive devices. In addition, signal denoising, feature extraction, dimension reduction, and AI techniques utilized for EEG-based BCI are evaluated. Moreover, Bagging and Adaboost are utilized to classify MI task for BCI using EEG signals. Different classifiers are used to enhance the performance of detecting the signals from the brain and make it on the real time and controlling any lateness. MI related brain activities can be categorized efficiently via AI techniques. This paper utilizes wavelet packet decomposition feature extraction approach to improve MI recognition accuracy. The proposed approach classifies MI-related brain signals using ensemble techniques. The results show that the proposed framework surpasses the traditional machine learning approaches. Furthermore, the proposed Adaboost with k-NN ensemble approach also yields a greater performance for MI classification with 94.57% classification accuracy for subject independent case.**

Keywords*— *Adaboost; Bagging; Brain–Computer Interface (BCI); Electroencephalogram (EEG), Motor imagery (MI); Multi-scale Principal Component Analysis (MSPCA); Wavelet Packed Decomposition (WPD).

I. INTRODUCTION

A brain-computer interface (BCI) is a development technology is known as the brain-gate. BCI is a connection path among brain and an external device. BCI devices are rely on brain signals that can transfer or take this signal to return function or movement to guide implanted prosthetic devices as natural limbs. In last years, BCI is a great achievement in medical research and also in enabling the individuals without disabilities to perform their tasks like walking and so forth just by thinking through creating a interaction link between a computer and a subject [1].

A BCI system observes electrical brain activities by using electroencephalogram (EEG) signals and detecting patterns, which produced by the user. The causes of use an EEG to measure brain signals are facilitate of use, great time resolution, and lower cost than other modalities like fMRI [2].

A BCI enables people to control peripheral devices such as spelling devices or virtual environments, robots using EEG signals. Numerous EEG signals can be employed to control BCI. BCI systems primarily use motor imagery techniques to generate event-related synchronization (ERS) and event-related desynchronization (ERD) within EEG alpha and beta frequency ranges of the brain signals. This form of BCI is usually employed for cursor control in virtual environments or on wheelchair navigation and computer screens. Usually, various motor imagery approaches, such as mental counting, tongue movement, left/right hand movement and foot movement are utilized [3].

BCI is devoted to help subjects with brain disorders, such as amyotrophic lateral sclerosis (ALS), cerebral palsy, and motor neurons disease (MND). EEG is frequently employed as a tool for the BCI system with non-invasion, comfort, low cost and low power consumption [4], [5]. In practice, based on phenomena of ERS and ERD, scientists can explain and characterize motor imagery (MI)-related brain signals. The execution or imagination of movement induces ERD/ERS, and both phenomena reflect as the changes in the oscillatory EEG voltage. ERD/ERS may therefore be characterized by a temporal or frequency analysis to classify MI tasks [6].

BCI is a powerful bridge that bypasses the human body, between the brain and the environment. This system may also be used as an alternative means of communication to enhance the quality of life of people with ALS, stroke and some other neuro-muscular disorders, which can change the way we interact, entertain which live dramatically in the future. BCI schemes can be invasive and non-invasive. Owing to the conveniences of use, most recent work focuses on the area of non-invasive BCIs. The three key noninvasive BCI approaches are the steady-state visual-evoked potentials (SSVEPs), event-related potentials (ERP), and the slow cortical potentials (SCPs) [7].

MI is described as the ability of the human brain to resynthesize motor events in the absence of visible movement. MI is an adaptable and practical tool for exploring processes of human cognition and motor activity since such mental imagery may occur consciously as well as be formed and directed consciously by a person. According to previous scientific works, MI employs almost the same neuronal framework as motor execution, allowing MI training to influence motor activity. BCI based on motor imagery employs fluctuations in cortical sensorimotor rhythms (SMR), which are typically event-related desynchronization (ERD) connected to various sensorimotor events, including motor imagery [8].

Furthermore, BCI has the potential to act as a technological connection for the control of Active and Assisted Living (AAL) systems in the context of intelligent settings and smart homes. To enhance BCI acceptability and efficacy, the user must see BCI-enabled control as easy and natural as feasible, much like any other typical AAL device interface [9].

EEG-based detection of MI signals includes feature extraction and classification. Feature extraction is the extremely crucial aspect of brain signal classification since it has a significant impact on classifier performance and computational complexity. The inclusion of features that are unrelated to the features extracted from the EEG will reduce the performance of the classifier. The number of features adds to the complexity of the classifier's calculations. Thus, it is essential to extract the optimal number of relevant brain signal features in order to achieve excellent classifier performance and reduced computational complexity. Nevertheless, the features obtained from brain signals contains noise because of the low signal-to-noise ratio of the brain signals, which can cause to an increase in the classifier's computational complexity and also to a reduction in classification accuracy [10].

In this paper, we utilize wavelet packet decomposition (WPD) to create numerous sub-band components from which six different statistical features are extracted. Finally, Bagging and Adaboost *ensemble* machine learning techniques are used for the classification task. Furthermore, the statistical characteristics determined from these sub-band coefficients show additional proof of differentiation between different imagery tasks. The performance of the developed structure was assessed on the dataset IVa of BCI competition III.

The rest of this paper is organized as follows: Section II introduces the literature review and Section III describes the material and methods. Data processing and the experimental results are explained in Section IV. Finally, the conclusions are outlined in Section V.

II. LITERATURE REVIEW

The most troubling consequences to the nervous system from injury or disorder are the loss of motor function. Over the last decades the EEG controlled assistive devices enabled artificial protheses, wheelchairs and computers to be controlled utilizing the brain's electrical activity. But those artificial devices' performance is lower compared to the speed and accuracy of actual limb movements. In a practical BCI-based motor imagery system, the user imagines moving various parts of the body such as leg or hand movements and the computer realizes how to differentiate several patterns of the brain activity that is simultaneously acquired. Since the BCI's primary goal is to use the EEG signals and generate the required instructions to control the external devices. The most critical application is to bypass the body's damaged parts or energize the partially paralyzed organs. BCI systems are seen as an exemplary solution to contact for people with multiple neuromuscular disabilities, such as cerebral palsy, amyotrophic lateral sclerosis, spinal cord injury, and stroke [11].

In this regard, a unique approach for automatic identification of MI tasks is developed by Subasi and Mian Qaisar [12]. They combined ensemble learning-based classifiers, Wavelet Packet Decomposition (WPD) feature extraction and Multiscale Principal Component Analysis (MSPCA) denoising for MI task classification. EEG signal segmentation and denoising is needed. The MSPCA is utilized a Daubechies algorithm-based wavelet transform (WT) for denoising. The WT is employed with the five level of decomposition. Each sub-band's statistical properties, namely standard deviation, mean absolute value, skewness, kurtosis, and average power are chosen. In addition, ratios of absolute mean values of adjacent sub-bands calculated and combined with other extracted features. Lastly, for the identification of MI tasks, the ensemble machine learning technique is utilized. The BCI competition III, MI dataset IVa are used to assess effectiveness. The results show that the proposed ensemble learning strategy achieves 98.69% and 94.83% classification accuracies for subject-dependent and subject-independent cases respectively.

Behri et al. [13] developed an effective BCI system that uses EEG data as brain commands. EEG signals can change due to various types of brain processes, influencing classification performance. The signal is improved in this study by using MSPCA. The WPD is employed to extract features from the augmented signal. The extracted features are used to investigate the efficiency of several classifiers in the categorization of EEG data obtained from five different individuals whilst aiming to move their right hand and foot. The overall classification accuracy is used to compare the findings. It is demonstrated that an efficient combination of MSPCA denoising, WPD feature extraction, and Random Forest classifier produces 98.45% classification accuracy. According to the findings, the proposed technique is a viable alternative for the design and development of future BCI systems.

Thenmozhi and Helen [14] combined spatial-related, time, and frequency MI characteristics to construct a consistent BCI system. The suggested technique employs the XGBO technique for feature selection and the random forest algorithm for EEG data classification. The effectiveness of the developed approach was evaluated using two available BCI datasets namely BCI Competition III dataset IIIa and dataset IVa. A new XGBO method improves accuracy while decreasing time spent by lowering feature dimensionality. The suggested approach picks the fewest characteristics possible to enhance the computational efficiency of MI-based BCI devices. The suggested approach is compared to recursive feature elimination, sequential forward selection, ANOVA, and LASSO techniques, and its accuracy is enhanced while requiring the less amount of computing time. For Datasets IIIa and IVa, the developed technique yields mean accuracies of 94.44% and 88.72%, respectively, and classification errors of 5.56% and 11.28%. It surpasses four state-of-the-art approaches, increasing accuracy by 0.87% and 0.59% for Datasets IIIa and IVa, respectively.

To classify right and left hand motor imaginary movements from brain signals, Dagdevir and Tokmakci [15] developed a new technique based on Truncation Thresholds (TT) approach with Empirical Mode Decomposition (EMD) and statistical Common Spatial Pattern (CSP) feature extraction technique. The TT approach is utilized to adjust the selected local minimum and maximum points using EMD in order to differentiate more precisely the hidden information about the motor imagery across the frequency domain sub-bands and remove the blinking electrooculography (EOG) artifacts. The CSP approach is used to extract statistical spatial information from each Intrinsic Mode Function (IMF) obtained by using EEG data with the EMD approach. Lastly, the collected features are input into three classifiers: k-NN, SVM, and LDA. The suggested approach utilised prepared dataset as well as the BCI Competition IV-2b dataset. The findings reveal that the suggested approach achieves 97% with the LDA classifier for the utilized dataset and 94% accuracy with the k-NN classifier for the BCI Competition IV-2b dataset, respectively.

Idowu et al. [16] presented a neuro-evolutionary method based on modified particle swarm optimization (MPSO) and feature extraction by CSP. They used BCI signals from four trans-humeral amputees to validate the suggested approach. Following the extraction stage, the data from five MI tasks were input into a wrapper-based neuro-evolutionary framework. When compared to other models such as genetic algorithm, particle swarm optimization, simulated annealing, and ant colony optimization, the MPSO performance data show that it is the best with the most significant outcomes.

Chaudhary et al. [17] presented a novel method for classifying different MI tasks based on brain signals utilizing the flexible analytic wavelet transform (FAWT) methodology. Multiple classifiers use the FAWT-based features as inputs. The best and most robust classifier for distinguishing right foot (RF) and right hand (RH) MI tasks is the subspace k-Nearest Neighbour (k-NN) classifier. The ensemble technique-based subspace k-NN classifier is used to determine the optimal performance parameters for the sub-band (SB) features. The fourth SB has the best parameter results: accuracy 99.33 %, sensitivity 99.6 %, specificity 99.6 %, F1-Score 0.9925, and kappa value 0.9865. The subspace kNN classifier produced substantial results in the other sub-bands as well.

For the detection of motor imagery patterns, Li et al. [18] suggested a unique approach that incorporated a frequency band selection CSP algorithm and a particle swarm optimization least squares twin SVM classifier. To achieve the most distinguishable features, they applied self-adaptive artifact removal and the CSP technique. The classifier's hyper-parameters were tuned using a genetic algorithm, a quantum genetic algorithm, PSO and chaotic PSO. BCI Competition IV data sets 2A and 2B are used to assess the suggested technique. According to the experimental results, the developed approach improves the average classification accuracy of data set 2A by 6.10%, 6.71%, 3.87%, 4.01%, 2.55%, and 4.86% when compared to the results attained by regularization projection twin SVM, SVM, LDA, ANN, and probabilistic neural network, respectively. Utilizing data set 2B, the strategy improved average recognition accuracy by 4.73 %, 5.46 %, 4.45 %, 4.10 %, 8.62 %, and 4.27 %, respectively.

Signal-dependent orthogonal transform (linear prediction singular value decomposition) is utilized for feature extraction in [19]. The mapping is defined by the transform as the LP coefficient filter impulse response matrix's left singular vectors. The collected characteristics are categorized into one of four MI movements utilizing a logistic tree-based model classifier. The suggested technique was initially compared to two similar state-of-the-art feature extraction methods, such as adaptive autoregressive (AAR) and discrete cosine transform (DCT) techniques. The LP-SVD strategy beat the other alternatives by a wide margin, reaching an accuracy of 67.35%. They increased the retrieved feature subset by integrating Q- and Hotelling's T2 statistics of the converted BCI signals to enhance the discriminatory ability of the extracted features and minimize computing complexity.

Kevric and Subasi [20] used Discrete Wavelet Transform (DWT), EMD, and WPD for feature extraction in a BCI framework. For this aim, the BCI competition III dataset IVa was employed. The MSPCA approach was used to remove noise. Furthermore, several sets of features were created to investigate the impact of a specific group of features. The technique of selecting parameters for signal decomposition algorithms was also clearly described. The combination of MSPCA de-noising and statistical features generated from WPD sub-bands achieved 92.8 % classification accuracy.

III. Materials And Methods

A. Dataset IVa of BCI Competition III

Dataset IVa of the BCI competition III [1] was collected from five healthy volunteers (labeled AA, AL, AV, AW, AY) who completed right-foot and right-hand motor imagery tasks. Brain signals from the four first sessions without feedback are included in this data collection. EEG data were collected using the 10/20 method. The data set contains 280 trials for each individual, including 140 trials for each task. Throughout each trial, the participant was instructed to do one of the right hand or right foot MI tasks for 3.5 seconds. Each subject had a training set and a testing set of varying sizes. The training set consisted of 168, 224, 84, 56, and 28 trials for subjects AA, AL, AV, AW, and AY, respectively, while the test set consisted of the remaining trials. The down-sampled data at 100 Hz is utilized in this investigation, but the original sampling rate is 1000 Hz.

B. Wavelet Packed Decomposition (WPD)

WPD is also considered as an extension of DWT because it decomposes both approximate and detailed components. Although it is a small difference, it provides for both methods various number of sets of wavelet coefficient. While WPD produces 2^j sets of wavelet coefficients, DWT provides $j+1$ wavelet coefficient sets for j-levels [21]. However, WPD offers a better frequency resolution than DWT does for the signal that is decomposed since it might cause to lack important information in higher frequency components [20]. In this research, four decomposition levels have been chosen.

C. Bagging

Bootstrap aggregation (Bagging) is the most basic ensemble modeling technique, combining the most fundamental approaches to base model construction and aggregation:

• Bootstrap samples from the training set are used to generate base models.

• Combined using unweighted voting for the classification task and averaging for the regression problem

When utilizing stochastic base classification models, class label voting could be substituted with class probability averaging, resulting in a probabilistic variation of bagging. As long as the process remains unstable, this approach is likely to outperform single models produced using the same algorithm as base models and does not guarantee extreme prediction quality. For stable algorithms with insufficiently diversified base models, prediction quality may have minimal improvement or even a small loss. Other than instability, the modeling algorithm has no special constraints. Similarly, attribute selection is frequently unnecessary because more attributes give more options to generate many distinct models. This is a significant deviation from the norm when single models are built. Single models generated by such techniques may exhibit significant variance depending on the training set. There is always a capacity to generate a worse or better model for a marginally varying training set. Creating many models based on various data samples without integrating them into an ensemble and then picking the best one does not deliver a useful answer. This is due to the fact that model choice should be dependent on model assessment, which makes sense only for a repeatable modeling technique. Achieving low-variance performance estimates, which may be used for model selection, in particular, necessitates several training and assessment cycles. If the human readability of model is not necessary, and if computing elements allow for the creation of many models, as is customary for this method, it is sufficient to explain using bagging. Up to a certain point, growing the number of base models improves bagging ensemble performance, after which it stabilizes. This is the point at which the maximum amount of model diversity feasible with bootstrap samples is reached [22].

D. AdaBoost

The adaptive boosting (AdaBoost) technique is the most well-known instance of boosting, and it is suitable to two-class classification applications. We will assume that the set of classes is C = {0, 1}, despite the fact that it is more popular to give the method for the set of classes C = {1, 1} that makes several stages easier to write by implicitly using class labels. AdaBoost's instance and model weighting systems are crucial particular characteristics that it provides to generic boosting algorithms. The weight of the model h_i is determined by its training set weighted misclassification error, as estimated by the definition. This raises the weights of misclassified instances while decreasing the weights of successfully classified examples to varying degrees depending on the weight of model h_i. Instance weight updates are more comprehensive with more accurate (higher weighted) models. It is assumed that the modeling approach is weight sensitive and that instance weights do not have to add up to one. Likewise, the weighted misclassification error is

[1]https://www.bbci.de/competition/iii/desc_IVa.html

considered to be appropriately estimated without the need for instance weights to add to one. The process will be executed for a maximum of m iterations, however it may end sooner if a base model is not significantly better than random. Having such a weak model before attaining the highest number of base models indicates that no more progress is inevitable, and increasing the weight given to misclassified instances would deteriorate rather than alleviate the situation. The technique yields a list of developed models together with their weights, which can subsequently be utilized to forecast weighted voting decisions [22].

IV. Results And Discussion

A) Experimental Results

In this study, we develop a framework for classifying MI framework for classifying a BCI signal that utilizes the MSPCA for denoising, the WPD for feature extraction, Adaboost and Bagging ensemble models for classification. WPD feature extraction provides for more accurate characteristics to be provided to classification algorithms. EEG signals are utilized to assess the performance of developed models. When testing AI models, 10-fold cross validation is appled. The performance of classifiers is measured in terms of accuracy, F-measure, and area under the ROC curve (AUC). Table I contains a summary of the acquired results.

The Adaboost with k-NN algorithm achieves the highest classification accuracy, 94.88%, and Bagging with k-NN achieves 92.62% for the first subject, AA. Adaboost with SVM comes in second with an accuracy of 88.10%, Random Forest has an accuracy of 81.55 %, and C4.5 has an accuracy of 70.6 %. It is concluded that the combination of MSPCA denoising, WPD feature extraction and the Adaboost with k-NN delivers the best performance for the first subject.

The Adaboost with k-NN algorithm achieves the highest classification accuracy, 92.38%, and Bagging with k-NN achieves 89.40% for the second subject, AL. Adaboost with SVM comes in second with an accuracy of 83.57%, Random Forest has an accuracy of 75%, and C4.5 has an accuracy of 70.24%. It is possible to conclude that the proposed framework of MSPCA denoising, WPD feature extraction and the ensemble of Bagging and Adabost with k-NN deliver the best performance for the second subject as well.

The k-NN algorithm accomplishes the highest classification accuracy, 88.93%, and Bagging with k-NN achieves 87.14% for the third subject, AV. Adaboost with SVM comes in second with an accuracy of 82.98%, Random Forest has an accuracy of 73.93%, C4.5 has an accuracy of 63.21%.

The Adaboost with k-NN algorithm achieves the highest classification accuracy, 94.76%, for the fourth subject, AW. Adaboost with SVM comes in second with an accuracy of 84.52%, Random Forest has an accuracy of 74.76%, C4.5 has an accuracy of 66.79%. Bagging with k-NN achieved 91.90%.

The Adaboost with C4.5 algorithm achieves the greatest classification accuracy, 99.17%, for the fifth subject, AY. Adaboost with Random Forest comes in second with 98.21% accuracy, REP Tree has an accuracy of 97.38%, SVM has an accuracy of 92.14%. Bagging with C4.5 achieves 96.67% accuracy.

The Adaboost with k-NN algorithm achieves the highest classification accuracy, 94.57% for subject independent case. Adaboost with SVM comes in second with an accuracy of 89.60%. Bagging with k-NN has an accuracy of 92.43%. It is revealed that the proposed framework of MSPCA denoising, WPD feature extraction and the ensemble of Adaboost with k-NN delivers the best performance for subject independent case as well.

B) Discussion

The developed system must extract and utilize the most appropriate characteristics for identifying different brain activities. The results reveal that a unique combination of MSPCA denoising, WPD feature extraction, and the ensemble of Adaboost with k-NN algorithm yields the best performance for the MI-based BCI.

For BCI systems, reliable detection of brain instructions is critical. The created model outperforms a unique combination of MSPCA denoising, WPD feature extraction, and ensemble of Adaboost with k-NN in terms of classification performance. It reaches a maximum accuracy of 94.57% for subject independent case.

V. Conclusion

In this study, an automated method for MI-BCI categorization is developed. This study takes into account two EEG signal patterns that correlate to different brain activities. The results demonstrate that the recommended system, which consists of a unique combination of ensemble of Adaboost with k-NN classifier, WPD feature extraction, and MSPCA denoising, is the best one for classifying motor imagery brain activity for subject independent and subject dependent cases except fifth subject. The system can categorize two distinct forms of MI-BCI commands using EEG data with a high degree of precision. Using a smart combination of the Adaboost with C4.5, WPD, and MSPCA, a maximum accuracy of 99.17% is reached across fifth subject. When using a unique combination of the Adaboost with k-NN, WPD, and MSPCA, an accuracy of 94.57% is attained for subject independent case. The obtained results motivate the design and development of the suggested system in order to evaluate its contribution to the recognition of different motor imagery commands. We analyzed the performance results of several classifiers to demonstrate the efficiency and robustness of the suggested system. It is possible to infer that the developed system is an effective, easy, and potentially useful implementation that might be employed for the future production of BCIs.

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TABLE I. EXPERIMENTAL RESULTS FOR MI-BCI DATA CLASSIFICATION.

		Accuracy (%)		F-Measure		AUC	
		Bagging	Adaboost	Bagging	Adaboost	Bagging	Adaboost
AA	SVM	84.64	88.10	0.846	0.881	0.898	0.881
	k-NN	92.62	**94.88**	0.926	0.949	0.962	0.949
	RF	79.05	81.55	0.79	0.815	0.879	0.897
	C4.5	69.76	70.60	0.698	0.706	0.764	0.773
	REP Tree	66.55	65.12	0.665	0.651	0.727	0.73
	RT	70.60	61.07	0.701	0.61	0.764	0.611
AL	SVM	80.71	83.57	0.807	0.836	0.846	0.836
	k-NN	89.40	**92.38**	0.894	0.924	0.937	0.924
	RF	74.88	75.00	0.749	0.75	0.825	0.827
	C4.5	69.05	70.24	0.69	0.702	0.767	0.779
	REP Tree	67.74	66.43	0.677	0.664	0.758	0.738
	RT	68.57	64.52	0.685	0.645	0.755	0.645
AV	SVM	79.17	82.98	0.792	0.83	0.858	0.83
	k-NN	87.14	**88.93**	0.871	0.889	0.919	0.889
	RF	72.38	73.93	0.724	0.739	0.798	0.805
	C4.5	62.50	63.21	0.625	0.632	0.678	0.678
	REP Tree	63.21	60.48	0.632	0.605	0.674	0.655
	RT	61.67	58.10	0.613	0.581	0.665	0.845
AW	SVM	79.05	84.52	0.79	0.845	0.847	0.948
	k-NN	91.90	**94.76**	0.919	0.948	0.953	0.829
	RF	73.57	74.76	0.736	0.748	0.812	0.726
	C4.5	65.71	66.79	0.657	0.668	0.714	0.726
	REP Tree	62.86	66.79	0.629	0.668	0.684	0.677
	RT	73.33	61.90	0.733	0.619	0.812	0.78
AY	SVM	89.40	92.14	0.894	0.921	0.937	0.921
	k-NN	89.05	91.19	0.89	0.912	0.928	0.912
	RF	95.71	98.21	0.957	0.982	0.994	0.998
	C4.5	96.67	**99.17**	0.967	0.992	0.99	1
	REP Tree	91.79	97.38	0.918	0.974	0.975	0.996
	RT	91.43	86.43	0.914	0.864	0.978	0.864
ALL	SVM	86.05	89.60	0.86	0.896	0.905	0.896
	k-NN	92.43	**94.57**	0.924	0.946	0.956	0.946
	RF	78.45	79.24	0.785	0.792	0.865	0.882
	C4.5	68.52	70.64	0.685	0.706	0.765	0.785
	REP Tree	67.21	69.29	0.672	0.693	0.744	0.756
	RT	68.36	63.69	0.681	0.637	0.755	0.637