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EXPLORING REGULARIZATION AND CHANNEL OPTIMIZATION IN MOTOR IMAGERY EEG

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ABSTRACT :
Through electroencephalography (EEG) signals, motor imagery (MI) can be seen as a non-invasive channel via which people direct their psychological activity to interact with the environment in an unmanual way, so they are valuable instruments for BCIs. EEG signals, on the other hand, present difficulties in correct identification and modeling since they have a low signal-to-noise ratio and are nonstationary. Whereas earlier works center on the use of CNN as a determining factor for the emergence of multimodal selection, this study compares the efficacy of classical machine learning techniques against deep learning methods: ANNs and their hybrids on connecting motor imagery performance. Furthermore, it delves into fusion of ensemble and hybrid models that improve performance across several iterations. The outcomes reveal that although CNN-based approaches offer strong spatial and temporal birth disambiguation, better precision and usefulness result from combining conventional and deep learning models, therefore surpassing those based on CNN. The study emphasizes how critical it is for innovative techniques to address brain signal problems and in which potential ways they could be further verified in BCI uses.

Keywords : mongrel ,conception, component, delicacy

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I. INTRODUCTION

Without doing the physical labor really, motor imagery is a mental rehearsal where one images doing a task or body movement that engages the neural system. Used sometimes after a stroke to help reverse loss of arm, hand, and other extremity movement so performance efficiency and communication might be improved.

By activating neural networks and visualizing motions without physically doing them, motor imagery serves as a therapy method that strengthens immobile limbs. They have shown to be helpful in the post-stroke period for early communication restoration and recovery of lost upper limb motor function. For example, mostly in the sensorimotor cortex and the alpha and beta bands, non-invasive electroencephalographic measures event-related synchronizations/desynchronizations (ERS/ERD) can somehow be followed in effect. Developing brain-computer interfaces (BCIs) that convert imagined movements into instructions driving prosthetic limbs capable of operating the devices also use these patterns; hence another way a user could detract from or disturb their environment is introduced.

II. II.RELATED STUDY

Deep Learning Techniques in MI-BCI Systems :[1]

In the study done by Ali Al-Sayegh, the focus was on applying deep learning approaches to motor imagery-based EEG classification. The researchers provided a thorough examination of various deep learning methodologies, highlighting the advancements and challenges in achieving higher classification accuracy. They concluded that while deep learning significantly improves the performance of MI-BCI systems, challenges remain in refining these methods for practical applications.

Advances in Ml-BII techniques : [2] J. G and P. Ramoser J. Pfurtscheller explored the most recent developments in motor imagery for brain-computer interfaces. The practical uses of recent innovations were underlined by the authors of the document, who also offered developments in classification methods, feature extraction techniques, and signal processing algorithms for EEG data.

Channel Choice Strategies in MI-BCI : Inquire about by Muhammad Zeeshan Baig et al.. The consider secured a run of strategies pointed at optimizing the determination handle to improve the execution and utilize of BCI frameworks, especially for communication errands and control assignments.

Adaptive Channel Selection for MI Classification : Yongquan Xia, Jianhua Dong, and Duan Li proposed an innovative approach to motor imagery classification by integrating adaptive channel selection with a graph-based ResNet algorithm. Their research demonstrated how this combination can improve the efficiency and accuracy of MI-BCI systems.

III. USAGES

This segment is to talk about around the dataset utilized and the proposed approach which is utilized to character the engine symbolism activity and its classification.

3.1 DATASET PORTRAYAL

To assess the adequacy of the proposed show, two well-known engine symbolism EEG datasets were utilized as benchmarks. The subtle elements approximately the dataset utilized is as takes after:

3.1.1 BCICIV Dataset

The BCICIV database is the following set of data crucial for BCI studies, especially motor imagery. The data is focused on the one subject that performed imagined hand gestures and the corresponding labels for each trial. This dataset have received significant attention for the purpose of training and testing BCI machine learning models. The dataset feature in this study is a subset so monolithic EEG recordings of one subject, who happened to perform 57888 trials at different time stamps, were collected. The subject column indicates the subject of the study whose subject ID is 9, the time column records delightful data of events during the recording. The main interest is on motor imagery tasks shown in label column. Each label is the kind of movement "Tongue" that subject was imagined to do. Age column is the trial specific data column which is very important for this task-based brain activity analysis.

EEG signals have been recorded from 23 electrodes placed according to the international 10-20 system, recording brain activity from various scalp locations.The high temporal and spatial resolution of this data makes it ideal for analyzing the neural patterns implicated in motor imagery, thus developing BCI systems and advancing understanding of how imagined movements are represented in EEG signals.

3.2 METHODS USED

This research employs a variety of machine learning and deep-learning algorithms to provide an interpretation of motor imagery tasks from EEG data by taking advantage of the BCI competition IV, 2a dataset. The data set contains 57,888 samples of the EEG recording done from 23 electrodes placed above the scalp;a huge source of information for distinguishing between different motor imagery tasks. These electrodes are recorded as EEG-Fz, EEG-C3, EEG-Cz, EEG-C4 etc. These electrodes capture electrical activity from the brain of the subject while he/she imagines movements like tongue movement.

1.STANDARDIZATION

X = $(x - \mu)/\sigma$, where μ - mean, σ standard deviation.

2.RANDOM FOREST CLASSIFIER

H(D) = $\sum_{i=1}^{n} pilog2(pi)$,where pi is the probability of each class

3.GINI IMPURITY

Gini(D)=1−∑ pi^2

4. ACCURACY

$$\frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

5. CLASSIFICATION REPORT

a. Precision

$$\frac{\text{(True Positives + False Positives)}}{\text{True Positives}}$$

b. Recall

$$\frac{\text{True Positives}}{\text{True Positives + False Negatives}}$$

c.F1-Score

$$\frac{2 * \text{Precision} * \text{Recall}}{\text{Precision + Recall}}$$

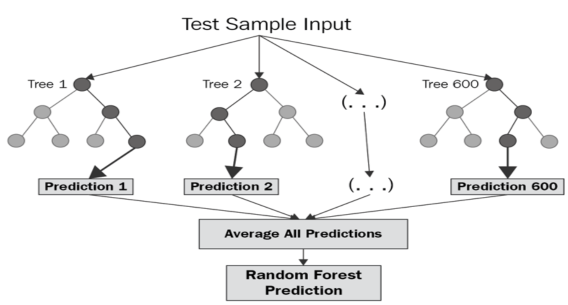
V. MACHINE LEARNING

5.1 IRREGULAR TIMBERLAND CLASSIFIER

The shoots of the Random Classifier Workflows that is the Irregular Woodland Classifier stem from a Random Forest Classifier. For the intended purpose, trees are created during an ensemble of decison trees traverse each iteration. The bootstrapping technique is usually applied to train each tree with a differently selected sample of data. One of the things that this procedure allows for is the removal of all the uniformity across the trees, as it allows several data points to be included and others to be omitted.

ALGORITHM :

The first step in the algorithm's implementation is scanning the data from a CSV file into a Pandas DataFrame. Following the training and testing split of the newly prepared dataset, and target labels and focus is separated, a project is set out to determine the efficiency of the model. Thereafter, a machine learning pipeline is created that would incorporate two main parts: standardization for the correct scaling of some features and the Random Forest Classifier model for the appropriate predictions. The last step in this section is to pass the training data into the newly trained Random Classifier to pitch the model. Lastly, the test data is passed to the model to measure its accuracy in segregating the data.



5.2 XGBOOST :

XGBoost has been one of the most significant and efficient learning algorithms in practice, with superlative ability to work at its best performances on structured or even unstructured data. It functions based on a boosting principle or ensemble style that predicts fineness as it combines different weak learners: often shallow trees. In an XGBoost scheme, the various weak learners successively train because each new tree fastens into correcting the crimes made by the former 'bones'.

One of XG Boost's name features is the objectification of regularization ways, particularly L1(Lasso) and L2(Ridge) penalties, [3] directly into its objective function. These styles of regularization help regulate the complexity of the model.

ALGORITHM :

The algorithm begins with data preparation. This process loads the dataset and splits it into training and testing sets. The feature scaling will then be carried out through standardization, meaning the features will be made to have a mean of zero and a standard deviation of one. Then comes the model configuration step, in which the XGBoost classifier is initialized. Then the model will be fitted on the training data using the fitting method. Finally, the model is evaluated by determining its accuracy as well as predicting results for the test data.

model.fit(Xtrain, Ytrain)

Accuracy=Total Predictions

Correct Predictions

5.3 ENSEMBLE METHODS

Ensemble styles in machine literacy improve predictive performance by aggregating multiple models to leverage their strengths and minimize sins. [11] Bagging, or Bootstrap Aggregating, is training a number of instances of the same model on random subsets of data created by slice with relief, and summing up their predictions to reduce friction and aid overfitting, as illustrated in styles like Random timbers. Conversely, boosting is a sequence of building models, where each new model corrects the crimes of its predecessors by chaining on misclassified cases, which reduces bias and friction considerably. AdaBoost and Gradient Boosting are prime examples of this.

VI.DEEP LEARNING

6.1 ANN CLASSIFIER

The ANN is a deep literacy model that takes inspiration from the mortal brain, capable of performing intricate bracket tasks. It consists of an input subcaste, retired layers, and an affair subcaste. The input subcaste analyzes features, and the retired layers use weights and activation functions such as ReLU, sigmoid, or tanh to learn patterns. ReLU is mainly used for its simplicity; sigmoid is good for double bracket, and tanh centers the data around zero. The affair subcaste produces the final vaticination using Softmax formulti-class problems or sigmoid for double bracket. 6.2 MLP CLASSIFER

The Multi-layer Perceptron (MLP) Classifier is a versatile neural network model used for classification tasks.It operates through a structured architecture consisting of an input layer, multiple hidden layers, and an output layer. The input layer receives the feature vectors from the dataset, where each neuron represents a distinct feature. The hidden layers can contain any number of neurons in varying sizes. This architecture enables the model to capture the complex patterns

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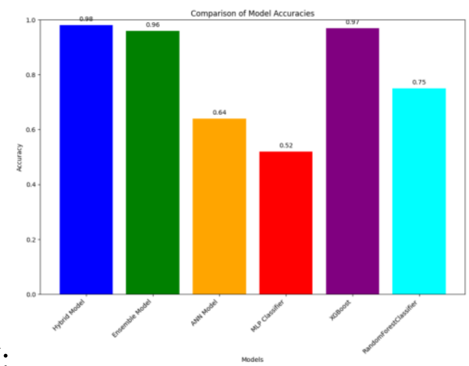
and relationships in the data. Each neuron in these layers computes a weighted sum of its inputs, applies an activation function like ReLU, sigmoid, or tanh, and passes the result to the next layer. In this way, the network models intricate non-linear relationships that simpler models might miss. This last layer is going to produce the output, which for a multi-class problem will likely have a softmax activation function.

6.3 HYBRID MODEL

By combining three types of classifiers that are cold-blooded, this will create the cold-blooded hybrid model: the Random Forest Classifier, the XGB Classifier, and the MLP Classifier.

Each of these classifiers brings its own strengths to the table—Random Forest is great at managing high-dimensional data, XG Boost is known for its effective boosting and strong predictive accuracy, and the MLP Classifier, which is a type of neural network, is adept at capturing complex non-linear patterns. The ensemble system combines these base classifiers and feeds their predictions to a meta-model, which is usually logistic regression, in order to generate the final prediction.

COMPARSION OF DEEP LEARNING AND MACHINE LEARNING :



GRAPH:

On observing all the algorithms the best one can be XG Boost and the Hybrid Model.

For Hybrid Model :

Classification Report:

	precision	recall	f1-score	support
0	0.98	0.98	0.98	2834
1	0.98	0.99	0.98	2898
2	0.97	0.97	0.97	2976
3	0.98	0.97	0.97	2870
accuracy			0.98	11578
macro avg	0.98	0.98	0.98	11578
weighted avg	0.98	0.98	0.98	11578

For XG BOOST:

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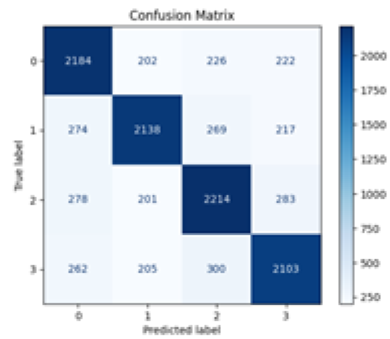
Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.98      0.98      2834
           1       0.98      0.98      0.98      2898
           2       0.97      0.96      0.97      2976
           3       0.97      0.97      0.97      2870

    accuracy                           0.97     11578
   macro avg       0.97      0.97      0.97     11578
weighted avg       0.97      0.97      0.97     11578
```



S.no	Algorithm	Accuracy	Precision	Recall	F1-Score
1.	Random forest	74.5%	75%	75%	75%
2.	Ensemble model	96.54%	97%	97%	97%
3.	XG boost	97.4%	98%	98%	98%
4.	MLP classifier	57.33%	57%	58%	58%
5.	Ann model	68.14%	69%	69%	69%
6.	Hybrid model	97.75%	98%	98%	98%

VII. FUTURE WORKS

More advanced algorithms may be implemented for performance improvement in research on motor imagery. CNNs can be used to detect spatial features from EEG efficiently, and RNNs and LSTM networks can be effective in capturing temporal dynamics. Long-range dependencies in recognition might be enhanced by more developed motor models, and autoencoders may be helpful for feature extraction or even dimensionality reduction. Techniques like XGBoost and Support Vector Machines (SVMs) could serve as strong classifiers or be integrated into ensemble methods. Graph Neural Networks (GNNs) might help identify spatial relationships between EEG channels, and Bayesian Neural Networks could aid in uncertainty estimation. Hybrid models that combine deep learning with traditional machine learning approaches, along with reinforcement learning for adaptive modeling, could further improve system performance.

VIII.SUMMARY

The creation of a hybrid model using an ensemble approach, as outlined in the law, effectively combines various machine learning algorithms to improve predictive performance. By integrating the strengths of Random Forest, XGBoost, and Multi-Layer Perceptron classifiers with a Random Forest meta-model, this method utilizes different learning strategies to enhance accuracy and robustness. Each individual model contributes its unique strengths—Random Forest's reliability, XGBoost's effectiveness with complex data, and MLP's ability to capture non-linear relationships—while the ensemble method refines the overall predictions through the meta-model. Standardizing the data with a Standard Scaler ensures that all features contribute equally to the model's performance. The final evaluation using accuracy and ranking criteria demonstrates the effectiveness of this hybrid approach in providing a comprehensive and reliable solution to ranking problems. This system not only enhances predictive accuracy but also offers a more robust outcome.protean and adaptive approach to handling different and complex datasets.

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