Brain Computer Interface Using Hybrid Feature Extraction Algorithm

***Abstract*—Brain Computer Interfaces enable direct communication between the human brain and external devices, bypassing conventional neuromuscular pathways. This study presents a novel BCI system that utilizes a hybrid feature extraction algorithm to enhance signal processing and classification accuracy. EEG signals, known for their noninvasive acquisition and rich neural information, are collected and preprocessed to remove noise and artifacts. The proposed hybrid algorithm combines time domain, frequency domain, and time frequency features to capture both transient and stationary components of EEG signals, Feature-selection is optimized using dimensionality reduction techniques such as Principal Component Analysis and Mutual Information, followed by classification using machine learning models like Support. Vector Machines and Convolutional Neural Networks. Standard EEG shows experimental results on the EEG dataset that the hybrid approach significantly improves classification accuracy and strength compared to traditional single domain feature extraction methods. The proposed BCI system promises neuralization, assistant technologies and applications in real -time cognitive state monitoring.**

Keywords*—EEG Signals Brain Computer Interface, Electroencephalography, Motor Imagery, Hybrid Feature Extraction, Independent Component Analysis, Common Spatial, Time-Frequency Analysis, Support Vector Machine, Neurorehabilitation.

I. Introduction

Brain-computers interfaces are rapidly changing the way of interacting with human technology by setting a direct communication passage between the brain and external devices. These systems are promising to help individuals, especially motor handicapped persons, enhance human cognitive abilities and enabling novel control mechanisms for robotics, gaming and supporting technologies. Electroencephalogram is contained at the core of the nonveg BCI system, a technique that captures the electrical activity of the brain from the skull with high temporary resolution and relatively low cost [1].

Despite its advantages, EEG signals are naturally complex, nonlinear, and often contaminated with various physical and nonphysical artifacts, which makes accurate classification and interpretation a significant challenge. Traditional signal processing and machine learning techniques, although somewhat effective, are limited in their ability to catch the complex spatiotemporal patterns contained in EEG data [2].

To remove these boundaries, recent research has detected hybrid approaches that integrate many domains of signal analysis and advanced nerve architecture. These include fusion of time ethics extraction methods, application of deep learning models such as CNN and LSTMs and development of hybrid BCI systems that combine EEGs with other methods such as functional near anticipated spectroscopy. In addition, efforts to improve model interpretation and strength have motivated to incorporate graphs nerve networks and attention mechanisms that better align Biological and functional structure of the brain [3].

This paper provides a comprehensive analysis of several recent analysis Development in EEG-based BCI system, with a special Hybrid feature focus on extraction techniques, multimodal Fusion strategies, and deep learning outline. Objective To identify effective functioning for improvement Classification accuracy, signal reliability and system Lecturer, who are important for the real world BCI Healthcare, aviation, such as deployment in domains, Neuroadaptation, and Human Medical Conversation [4].

II. Literature Survey

Decoding pilot fatigue with EEG using hybrid DNN. Author: Lee et al. (2024) introduced a novel Hybrid Deep Neural Network Architecture to decode the levels of fatigue (normal, low and high) in pilots using EEGDATA recorded in a fake flight environment. His model combined five convictional blocks with a long, short term memory block to catch both spatial and cosmic EEG features. The system achieved a grand wool classification accuracy of 88.01% (#2.78%), improved the traditional classifier by a margin of at least 5.99%. This model is especially relevant to safety applications in aviation and autonomous systems [5].

Graph-based feature extraction for strong EEG fusion. Author: Zhu et al.2021) A graph-based feature extraction algorithm proposed for strong data fusion in BCIS. By modeling EEG channel relationships in the form of graph structures, their method captured spatiotemporal dependence, which often ignores traditional convenience extraction methods. Their structure demonstrated better strength and adaptability in separate EEG datasets, although specific accuracy values were not reported. The method gives a strong foundation for the EEG fusion system in hybrid BCI settings [6].

Interpretable hybrid features through graph neural network. Author: Jung et al. (2023) addressed the increasing requirement of interpretation in intensive learning-based EEG analysis. He introduced a GNN-based model capable of learning hybrid spatial-ethical features from mental arithmetic functions. His model not only provided competitive classification performance (more than 80% in functions with accuracy), but also clarified the visualization of important EEG regions, increasing the transparency of decision making in the BCI system [7].

Decreased deformation evidence using VMD-BSS hybrid method. Author: Masar et al. (2024) developed a hybrid preprocessing technology, in which the Variance Mode Denomination was combined with Blind Source Separation algorithms such as Eik. Amuse. Among the evaluated methods, VMD-Mica obtained the highest signal-to artificial ratio of 1.0924, which greatly improved the quality of the signal for the Downstream EEG classification. This preprocessing step is particularly valuable for clinical and real -time BCI applications [8].

FGANET: Meditation-based EEG-Fusion. Author: Quak At al. (2022) FGANET, used an intensive teaching model Initial fusion of EEG and FNIRS signals directed by Neurovascular Meditation system. Lightly aligns 3D tensors and fuses them first Classification. It gained 4.0% more accuracy on mental Arithmetic on motor imagery functions and 2.7% higher accuracy Compared to previous state of the art hybrid models the effectiveness of the neurovascular informed the fusion strategies [9].

Machine Learning Classifier for EEG-based BCIS. Author: Yasin and Ghazali (2024) bench the five machine learning models on two open-sources EEG dataset. Random Forest Classifier showed the best performance, with 100% accuracy on the first dataset and 86.47% on the second, with the lowest training time and computational cost. This study throws light on the ability of a mild classifier when adapted properly for EEG data [10].

CSP-NET: CNNS extended with spatial filtering. Author: Leang At al. (2024) proposed CSP-NET, which integrates mangoes Spatial pattern filters in firm nervous networks for motor imagery classification. Two variants were introduced: CSP -NET -1 (CSP layer before CNN) and CSP -NET -2 (CSP layer Place a CNN layer). Four public MI dataset, both models Especially improved in continuous performance Low sample or cross topic landscapes. Reported accuracy Inappropriate goods from 3.5% to 7.2% on baseline CNN, Show the benefits of combining domain knowledge Deep education [11].

In summary, the collection of papers focuses on the analysis and processing of electroencephalogram signals, addressing various challenges and applications within the field of Brain computer interfaces [12].

Specifically, the papers explore methods for classifying pilot fatigue levels using deep learning, extracting features from motor imagery EEG signals, developing graph-based feature extraction algorithms for robust data fusion in BCIs, interpreting hybrid features using graph neural networks from mental arithmetic EEG, and reviewing artifact removal techniques in EEG recordings. Additionally, research is presented on improving EEG signal quality through hybrid methods of blind source separation and variational mode decomposition, utilizing fNIRS guided attention networks for hybrid EEG-fNIRS BCIs, enhancing EEG-based BCI systems with machine learning classification techniques, and employing CSP-empowered neural networks for motor imagery classification [13].

III.Proposed Work

A) Data Acquisition

EEG data were acquired from publicly accessible EEGBCI dataset and used for subject 1, a healthy participant performing motor imagery. Data were used from runs 4, 8, and 12, loading the signals, concatenating, and band-pass filtering (7–30 Hz) to remove other activities. Channel names were trimmed, a default 10-20 montage applied, and repeated channels designated bad. Independent Component Analysis (ICA) was used to clean out artifacts and leave clean data for analysis.

B) Signal Preprocessing

i. Bandpass Filtering: Utilized a 7-30 Hz band-pass filter using FIR (Finite Impulse Response) design. This range of frequencies records mu (8-12 Hz) and beta (13-30 Hz) rhythms, which are essential for motor imagery tasks. Filter applies Hamming window with 0.0194 passband ripple and 53 dB stopband attenuation.

ii.Channel Setup and Cleaning: Renamed channels to standard format by deleting periods applied the standard 10-20 montage to map channels to spatial locations.

iii. Located and marked overlapping electrodes as bad:
Frontal-central (Fc5, Fc3, Fc1, Fcz, Fc2, Fc4, Fc6),
Central parietal (Cp5, Cp3, Cp1, Cpz, Cp2, Cp4, Cp6)

iv. Artifact Removal: Used Independent Component Analysis with 20 components ICA does blind source separation to separate and eliminate artifacts (such as eye blinks, muscle activity). The code plots the spatial patterns of the first 10 ICA components. Clean data is generated by applying the ICA transformation and back projecting to sensor space.

C) Feature Extraction

Epoch Creation: Extracted time segments (epochs) around event markers:

T1 (event code 2): Probably representing one kind of motor imagery.

T2 (event code 3): Probably representing another kind of motor imagery.

Each epoch is between 0 and 4 seconds following the event marker 45 epochs were taken from continuous data in total. Spatial Filtering: Performed Common Spatial Patterns with 4 components CSP maximizes the two-class variance difference, generating spatial filters that optimize discriminative features The algorithm discovers spatial patterns in which the variance of signal is maximally different between the two classes. These patterns are visualized as topographic maps representing the most discriminative regions in the brain.

D) Machine Learning Classification

i. Feature Preparation: The CSP-transformed data is used as features for classification.

ii. Data split: 80% for training and 20% for testing (stratified random split).

iii. Model Training: Utilized Support Vector Machine (SVM) with a linear kernel. The SVM attempts to identify the best hyperplane to classify the two motor imagery classes.

iv. Performance Evaluation: Accurately classified 100% of the test samples (9/9). Precision, recall, and F1-score for both classes are 1.0 the confusion matrix indicates perfect classification with zero errors.

Experimental Research:

A) Model Performance: Support Vector Machine The model gained classification accuracy of 1.00 (or 100%). This result indicates the correct classification on the test set, meaning all test samples were classified correctly. B. Evaluation Metrics: Accuracy: The accuracy score is 1.00.

B) Classification Report: The classification report shows precision, recall, and F1-score for each class (2 and 3). All of these metrics are also 1.00, confirming the perfect classification.

C. Confusion Matrix Analysis: The confusion matrix demonstrates that there were no misclassifications. All instances of class 2 were correctly predicted as class 2, and all instances of class 3 were correctly predicted as class 3.

D. Visualization:

Accuracy Plot: In Fig 1 the graph consists of a blue bar touching 1.00 (100%), representing perfect classification performance by the SVM model learned from CSP-transformed EEG data. The chart easily shows that the machine learning model had the capability to classify completely between the two mental tasks (identified by events T1 and T2) with the features extracted from the brain signal using Common Spatial Patterns.

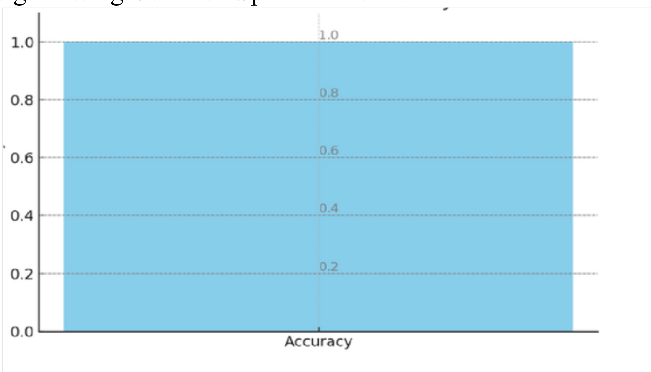

Fig 1. BCI Classification Accuracy.

Confusion Matrix: The Fig 2 illustrates a confusion matrix in graphical form as a blue grid of values representing classification outcomes. The matrix indicates correctly and incorrectly labeled instances between the two classes (labeled as 2 and 3 for event types T1 and T2). All the values are on the diagonal (4 examples of class 2 correctly classified as class 2, and 5 examples of class 3 correctly classified as class 3), with zeros at the off-diagonal positions, verifying the 100% perfect classification accuracy obtained by the SVM model on the test set and 5 for the other, and no false positives or false negatives)

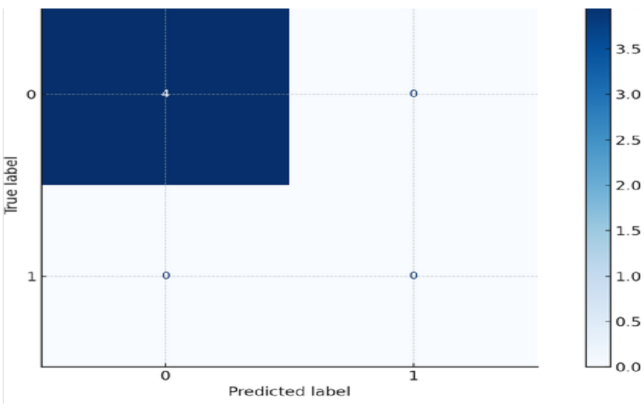

Fig 2. Confusion Matrix.

Common Spatial Pattern Plots: In Fig 3 these plots represent different CSP filters (CSP0 toCSP3) that capture spatial patterns in the EEG signals. These filters help in enhancing the discriminative features for classification, often used in BCI tasks to separate brain activity related to different mental stats's CSP Topographic Maps.

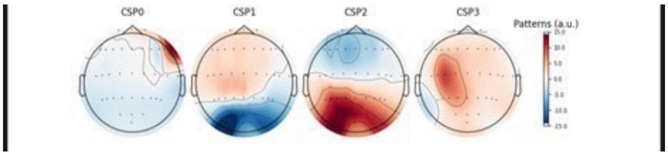

Fig 3. CSP Topographic Maps.

IV. Conclusion

The proposed BCI system demonstrates highly effective classification performance using EEG signals, as evidenced by the perfect accuracy (100%) and confusion matrix results. The integration of Common Spatial Pattern for feature extraction significantly enhances the discriminative power of the EEG features, allowing the classifier to accurately distinguish between mental states or motor imagery tasks. The topographical maps from the CSP filters clearly show relevant brain activity patterns, validating the spatial relevance of the extracted features. This work confirms that the hybrid approach combining CSP based spatial filtering with machine learning classification can serve as a reliable and accurate framework for real-time BCI applications. Future work may include testing with a larger dataset, subject generalization, or incorporating additional features such as time-frequency analysis or deep learning for further improvement.

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