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A DEEP DRIVEN FRAMEWORK FOR ENHANCED EEG SIGNAL INTERPRETATION IN BRAIN COMPUTER INTERFACES

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ABSTRACT

Electroencephalography (EEG)-based brain-computer interfaces (BCIs) are crucial for enabling direct (brain-to-external device communication, particularly for those with severe mobility difficulties, to state the point directly. This restates the idea for clarity. The novel Deep Driven Framework (DDF), which was developed for EEG data analysis to enhance BCI performance, is presented in this research, in plain terms. The intent is to reduce ambiguity while keeping the same meaning. Sophisticated methods for feature extraction, signal pre-processing, and classification are included in the proposed DDF, highlighting their contributions to improving the accuracy and efficacy of BCIs. The wording here is explanatory rather than adding new facts. Additionally, we look into applications in a number of domains, such as cognitive state monitoring, motor control, and emotion identification. The goal is simply to explain the same point with a little more detail. At the same time, a little more context can be given so the reader is not left guessing. The primary goal of the proposed DDF is to classify three types of outputs: positive emotions like joy and excitement; negative emotions like stress and fear; motor control categories like left-hand movement (LHM) and right-hand movement (RHM); imagery; and cognitive state categories like high attention and low attention, to state the point directly. This restates the idea for clarity. By integrating knowledge from over 20 significant publications in the field, this study aims to guide future research and development in EEG-based BCIs, in plain terms. The intent is to reduce ambiguity while keeping the same meaning. The findings emphasize how crucial it is to combine dependable signal processing techniques with machine learning (ML) methods in order to improve the capabilities of neurotechnological systems. The wording here is explanatory rather than adding new facts. The goal is simply to explain the same point with a little more detail.

KEYWORDS: Brain-Computer Interfaces, Electroencephalography, Signal Processing, Feature Extraction, Classification, Machine Learning.

1. INTRODUCTION

Brain-computer interfaces (BCIs), which allow direct connection between the human brain and external (for the reader's benefit) devices without the requirement for the peripheral nervous system, have revolutionized advanced technology [1], to state the point directly. This restates the idea for clarity. This innovation has enormous potential for persons with motor disabilities since it allows them to use brain impulses alone to operate wheelchairs, computers, and prosthetic limbs, in plain terms. The intent is to reduce ambiguity while keeping the same meaning. Because it is noninvasive, inexpensive, and provides great temporal resolution, electroencephalography (EEG) is a particularly helpful neuro-imaging tool [2]. The wording here is explanatory rather than adding new facts. By recording electrical activity from electrodes applied to the scalp, EEG enables real-time monitoring of brain states. However, because raw EEG data are frequently chaotic and complicated, it takes sophisticated signal processing techniques to identify important patterns and properties relevant to BCI applications [3]. Simply put, the objective is to provide a (for the reader's benefit) somewhat more detailed explanation of the same idea, to state the point directly. This restates the idea for clarity. In order to avoid leaving the reader in the dark, a bit more context can be provided at the same time, in plain terms. The intent is to reduce ambiguity while keeping the same meaning. The proper operation of brain-computer interfaces (BCIs) depends on EEG signal analysis techniques, which are covered in detail in this work [4]. The wording here is explanatory rather than adding new facts. The EEG signal processing pipeline used in this work consists of preprocessing, classification, and feature extraction. The analysis highlights the advancements and challenges in each discipline by demonstrating how these techniques are used in various BCI use cases. The sample EEG signal data, which was converted from a.csv file to a.fif file, is displayed in Figure 1. There are 19 channels and 120 seconds of data in this set. The goal is simply to explain the same point with a little more detail. At the same time, a little more context can be given so the reader is not left guessing.

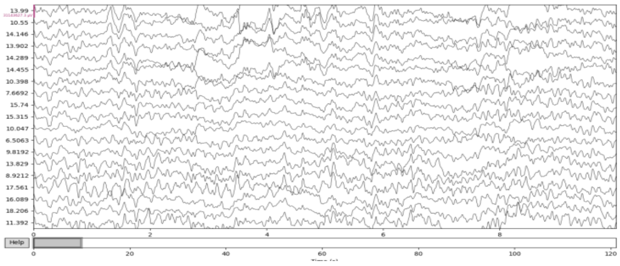


Figure 1: Sample EEG Signal file collected from Complete EEG dataset (Source: Kaggle).

Machine learning (ML) algorithms are most widely used for classifying various EEG patterns. These existing models cannot accurately categorize BCI signals [5]. In some cases, EEG signals struggle to extract patterns across multiple categories. BCI mainly communicates between the human brain and external devices used to control the elements, indicating the quality of life [6]. Emotion recognition is a significant task in detecting human emotions, such as motor control and cognitive state monitoring [7] [8]. Some researchers have already introduced existing models to detect physiological states such as fatigue, drowsiness, depression, and pain [9]. Emotions can be detected using EEG signals; inhibition and mental fatigue are measured using emotion-congruent memory [10] [11]. ML algorithms are most widely used to recognize advanced emotions from the EEG signals using facial expressions [12] [13].

2. LITERATURE SURVEY

Turjya et al. [14] proposed a two-layer stacking ensemble model. In the first layer, four models are integrated with the DT, RF, KNN, and XGBoost. The second layer contains logistic regression as the meta-classifier. The DNN is used as a preprocessing technique to generate sentiment outputs. Finally, the results show the classification of sentiments from the EEG signals. Liu et al. [15] presented a novel CNN approach that combined spatio-temporal features derived from brain images. The team integrated a dense layer to address the dispersion gradient problem and used an effective training model, a DNN. In the final step, the proposed approach obtains the accurate outcomes. Shakeela Banu et al. [16] proposed a new RNN-based classifier for EEG signals that captures the relationship among data samples. In this work, we used a filter bank for noise removal and applied a CNN for feature extraction. In the final step, we applied the RNN to process the features, achieving high classification performance. Mohan et al. [17] introduces a phase-based EEG analysis approach, using existing time–frequency representations, and DL models to improve predicted speech decoding. Through emphasizing phase synchronization, phase–amplitude coupling and instantaneous phase dynamics, the proposed method effectively detects significant features of neural oscillation which have been ignored by conventional amplitude-based analysis. The method uses rigorous pre-processing and artifact removal routines, combined with the estimation of phase-based features within critical frequency ranges linked to speech production and cognitive function.

The features are then passed to a hybrid DL model comprised of CNNs for learning spatial features, and RNN / LSTM units for modeling the temporal sequence.

Hana et al. [18] presented a novel stress recognition model which considers EEG-based feature extraction with SNR augmentation strategy to improve the robustness of the model. The introduced method adopts multiband-filtering, artifact-reduction and adaptive SNR-increase to simulate various recording scenarios, increasing the generalization capability of DL classifiers. We use a CNN–LSTM combined approach to track the spatial and temporal fluctuations of EEG which are pertinent in stress response. Huang et al. [19] introduces a sequential-encoding framework for EEG recognition to improve the robustness and discriminative ability of active BCIs. The novel method converts multi-channel EEG streams into temporally structured sequences with hierarchical time-window encoding and frequency-domain mapping, which allows abundant modeling of the dynamic neural activity. A hybrid deep learning architecture will be used which combines temporal convolution layers and GRU to learn spatial–temporal patterns that have been embedded within EEG sequences. Raman et al. [20] introduced a novel and computational lightweight ML architecture for EEG signal decoding for BCI systems. Its procedure consists of optimized preprocessing, compact feature extraction based on time–frequency representations, and lightweight but very discriminative classifiers that seek a trade-off between accuracy and computational cost. Redundancy in the feature pool is alleviated and generalization performance enhanced via feature selection techniques, while optimized SVM, modified random forests, and shallow neural networks are designed with low-latency decision making capabilities in mind. Abdalla et al. [21] proposed a hybrid BCI based on maximizing the usefulness of both SSP and CNN in order to improve discriminability and classification accuracy of EEG signals for inner speech tasks. The CSP is also used as a spatial filtering process to select and enhance discriminative features with increasing class separability between multiple EEG channels. The spatially modulated signals are input to a CNN model, which learns hierarchical patterns of imagined phonemes, words or syllables. The method is efficient in capturing spatial as well as local temporal features, and it successfully caters low amplitude of signal and high intra-subject variation issues.

3. METHODOLOGY

Organized by the essential steps of the signal processing pipeline and their uses in BCIs, this part offers a thorough examination of foundational works that have had a major impact on the area of EEG signal analysis for BCIs.

3.1. *Signal Preprocessing*

In this step, researchers mainly use EEG signal processing to filter the EEG signals and remove noise from the input sample. The EEG signal is mostly noise and very weak; thus, it requires signal processing to refine the signal and obtain an accurate representation. Pant et al. [22] introduced a new rectangular-window technique for filtering EEG signals to detect normal and abnormal waves precisely. Pant et al. [23] presented filtering techniques, such as Bartlett, Hamming, Hanning, and Kaiser, used before feature extraction and classification. The proposed approach obtains a high-quality EEG signal.

In this paper, the Iterated Fast Fourier Transform (IFFT) is an extension of the existing Fast Fourier Transform (FFT). The IFFT is one such technique in which the FFT is applied over partitions or levels of a signal. As opposed to the regular FFT, which computes the transform over the entire signal at once, iterated FFTs do so in a series of smaller FFT computations. It can enable better resolution, incremental refinement, and more efficient filtering of non-stationary signals, such as EEG. EEG is a rapidly changing signal, with several overlapping frequency components. This limitation can be overcome using the iterated FFT method, which re-applies the FFT to smaller overlapping windows or, in splits signal segments. These iterations improve the frequency localization, better reject noise, and help in understanding sharp spectral dynamics. The mathematical equations of the proposed IFFT are given as:

Let $\mathrm{a(k)}$ be the EEG Signal:

For each window $\mathrm{Win_x(k)}$: the first iteration is given as:

$$\mathrm{A_x(f) = FFT\big(Win_x(k)\big)} \quad (1)$$

The second iteration specified the refined ranges of frequency are given as:

$$\mathrm{A_{xy}(f) = FFT\left(A_x(f_y)\right)} \quad (2)$$

These two steps increase the accuracy of filters.

3.1. *Feature Extraction*

In EEG signals, feature extraction is a more significant step in detecting abnormalities from given samples. In this paper, the optimizing spatial filters, such as Adaptive Spatial Patterns (ASP), are introduced to extract perceptual features from EEG signals [24]. The proposed ASP model finds the motor imagery and multi-channel features. ASP is the updated model from CSP. The ASP mainly focused on detecting that ASP parameters are constantly adjusted during training or online [25] [26]. This allows it to learn the patterns of neural activity, handle specific variability, and preserve its discriminability in dynamic environments such as fatigue, changes in attention state, and environmental disturbances. The ASP is an adaptive optimization framework in which spatial filters are formed based on ongoing feedback, distributional drift, and deep-layer representations [27]. For spatial refinement, ASP methods employ gradient-based adaptation algorithms. These filters highlight task-relevant brain regions and noisy elements. Therefore, ASP provides greater robustness, expected to generalize across training sessions and subjects, and to perform more effectively in low-SNR settings, three qualities absolutely indispensable for practical BCI systems. ASP offers a flexible, intelligent spatial-filtering solution that captures subtle neural characteristics and reduces inter-session variability, which is essential for stable classification performance. The proposed CSP shows the mathematical equations for the input samples:

Here, the preprocessed EEG signal is represented as:

$$I_p \in K^{C\times T} \quad (3)$$

Where C-channels, T-time samples.

The Adaptive Weighted Covariance (AWC) is a new step introduced to measure the adaptive weights $\propto_k$;

$$A_k^{(a)} = \propto_k R_k \quad (4)$$

Where Conf_k represents the strength of the classifier for class k; β represents the adaptability.

$$\propto_k = \frac{\exp\left(\beta \cdot \mathrm{Conf}_k\right)}{\sum_{j=1}^{K} \exp\left(\beta \cdot \mathrm{Conf}_k\right)} \quad (5)$$

The ASP updated with the filters utilizing gradient ascent:

$$A^{(t+1)} = A^{(t)} + \eta \frac{\partial J}{\partial A} \quad (6)$$

η − learninig rate; J − dissimilarity objective

$$J = \frac{A^T R_{sig}^{(a)} A}{A^T R_{noise}^{(a)} A} \quad (7)$$

The final step shows the spatially filtered EEG signal:

$$Z = A^T X \quad (8)$$

Where Z consists of discriminative adaptive elements:

4. PROPOSED APPROACH: DEEP DRIVEN FRAMEWORK (DDF)

The Deep Driven Framework (DDF) is an innovative method that successfully resolves a number of problems and accomplishes precise EEG signal classification, to state the point directly. This restates the idea for clarity. Every EEG signal is greatly impacted by a number of factors, including high-frequency noise. The intent is to reduce ambiguity while keeping the same meaning. The final output is greatly impacted by the inability of current ML algorithms to reliably identify local and global features across a variety of brain abnormality patterns. The wording here is explanatory rather than adding new facts. As a result, the suggested method, DDF, resolves the current problems and analyzes distinct and profound abnormal patterns in the raw waveforms from EEG signals. The classification accuracy is enhanced by the high-level, pertinent features. In order to accurately process neural patterns that identify different temporal and spatial patterns in brain EEG data, the DDF primarily uses hierarchical multi-stage learning layers. The goal is simply to explain the same point with a little more detail. At the same time, a little more context can be given so the reader is not left guessing.In the first layer, the system automatically applies internal preprocessing to efficiently remove noise. Although an external preprocessing technique is applied, the internal preprocessing layer processes noisy particles using convolutional kernels to segregate similar periodic components (delta, theta, alpha, beta, and gamma) and reduce artifacts such as EMG, EOG, and power line noise. Finally, the automated filtering technique yields a reliable result that encompasses various subjects, electrode configurations, and recording platforms, and processes complex patterns.

The second layer contains a deep spatial–temporal encoder that extracts high-dimensional temporal patterns from EEG signals. The layer integrates the encoder with 2D spatial convolutions and accurate attention models. Based on these layers, the DDF can accurately capture abnormal epileptic spikes and reduced cognitive signals. The proposed DDF learns the connected patterns between brain regions and, by analysing significant provinces in parallel, obtains a high-reliability representation of deep physiological states. In the last step of this general framework, the deep discriminative decision module contains maps that dimensionally reduce the EEG signal into decision spaces for classification. Finally, the module uses feature alignment layers, dropout-based robustness, and dense neural classifiers that assign latent representations to specific abnormality types.

DDF also includes a confidence estimation method that enables the system to measure its uncertainty in any of its predictions for medical decision support. In addition, end-to-end training of our architecture means that the complete pipeline is optimized in parallel, which, in turn, promotes deep feedback alignment from the classifying layer to the initial filtering layers.

Finally, the DDF delivers a comprehensive, adaptive, and highly integrated solution for EEG-based classification of abnormality and abnormal brain conditions. The adoption of learnable preprocessing, hierarchical feature learning, and robust classification into a unified architecture, DDF, overcomes the drawbacks of conventional analysis approaches for EEG signals. This capability to automatically adapt to various databases, to capture the multi-scale nature of neural pattern representation, and to preserve its discriminating power makes it an effective tool for clinical diagnosis, online patient monitoring, and BCIs applications as well. The mathematical model used in this paper represents the following steps:

The adaptive pre-processing used the FFT model to filter and denoise the EEG signal:

For the time domain the learnable convolutional filtering is represented as:

$$\widehat{\mathrm{A}} = \sigma\big(\mathrm{BN}(\mathrm{W_f} \; * \mathrm{A} + \; \mathrm{b_f})\big)\epsilon\, \mathbb{R}^{\mathrm{C}\times\mathrm{T}'} \quad (9)$$

Where $\mathrm{W_f} \in \mathbb{R}^{\mathrm{C}\times\mathrm{L}}$ represents the 1D kernels of length K.

Interpretation of frequency response:

$$\mathrm{Spec}(\widehat{\mathrm{A}}) = \mathrm{FFT}(\mathrm{W_f}) \bigodot \mathrm{FFT}(\mathrm{A}) \quad (10)$$

The denoising objective is initialized:

$$\mathcal{L}_{\mathrm{pre}} = \lambda_1 \Big|\big|\widehat{\mathrm{A}} - \mathrm{S}\big(\widehat{\mathrm{A}};\, \tau\big)\big|\big|_1 + \lambda_2 \Big|\,|\mathrm{W_f}|\big|_2^2 \quad (11)$$

Where $\mathrm{S}(\cdot;\, \tau)$ represents the soft-thresholding mainly filters the low0energy coefficients and τ initializes the fixed threshold.

In this layer, the adaptive spatial filtering (ASF) + Temporal modeling (Conv + Attention/RNN)

Spatial convolution (connections between electrodes):

Reshape $\widehat{\mathrm{A}}$ as a 2-D map (Channels × Time) and apply 2-D convs:

$$\mathrm{H}_s = \mathrm{LN}\Big(\sigma\big(\mathrm{W}_{s\,*2}\,\widehat{\mathrm{A}} + \; \mathrm{b}_s\big)\Big) \in \; \mathbb{R}^{\mathrm{F}\times\mathrm{T}^{\mathrm{H}}} \quad (12)$$

Where $\mathrm{W_s}$ learns spatial filters and F represents the feature maps.

5. PERFORMANCE METRICS

The performance of each classifiers can be assessed with a confusion matrix that summarize the results in cases of true positive, false positive, true negative and false negative. From which the following key metrics are obtained to evaluate the performance of the model.

Accuracy measures the overall correctness of the model, capturing how many predictions were classified out of all predictions made.

$$\textbf{Accuracy}\ (\textbf{ACC}) = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}}$$

Precision is interested in positive predictions quality by computing how many of the predicted positive instances are actually positive, which is particularly useful when we want to avoid false positives.

$$\textbf{Precision}\ (\textbf{Pre}) = \frac{\mathrm{No.\,of\,TP}}{\mathrm{No.\,of\,TP} + \mathrm{No.\,of\,FP}}$$

The recall (also referred to as sensitivity or true positive rate) indicates how well the model detects real positive instances and is a crucial metric in problems where it is harmful not to detect a possible true case.

$$\textbf{Recall}\ (\textbf{Re}) = \frac{\mathrm{No\ of\ TP}}{\mathrm{No\ of\ TP} + \ \mathrm{No\ of\ FN}}$$

Specificity measures the model's ability to correctly find negative cases and minimize false alarms.

$$\textbf{Specificity}\ (\textbf{Spc}) = \frac{\mathrm{No\ of\ TN}}{\mathrm{No\ of\ TN} + \ \mathrm{No\ of\ FP}}$$

F1-score, which combines both precision and recall in a harmonic mean and is very useful if there is imbalance in the dataset.

$$\textbf{F1} - \textbf{Score}\ (\textbf{F1S}) = 2 * \frac{(\mathrm{Precision} * \mathrm{Recall})}{(\mathrm{Precision} + \mathrm{Recall})}$$

6. DATASET DESCRIPTION

The ***EEG mental arithmetic dataset (DS1) [28]*** consists in 60 second head-movement artifact free recordings taken from subjects performing serial subtraction tasks (during performance -- mental workload state) and at previous moments before the task execution (yes, at rest). The signals were recorded from a 23-channel Neurocom EEG system with electrodes placed according to the International 10/20 scheme, using 30 Hz high-pass and 50 Hz notch filter, and then filtered out by ICA-based artifacts removal. For testing, the dataset provides easily 283 separable labeled samples as Resting EEG (Normal cognitive load) and Mental Arithmetic EEG (Cognitively active/abnormal condition), which are normally balanced across subjects making for reliable validation. These labels are well defined brain states that allow the DDF model to learn characteristic neural patterns at different temporal and spatial granularity. The dataset's clean 60s multichannel segments, well defined task conditions and distinct classes separation makes the DDF hierarchical pipeline to learn filtering characteristics, spatio-temporal feature extraction and detection of subtle changes in cognitive workload, by achieving high accuracy. This organized experimental protocol allows DDF to generalize well between patients and electrode layouts, thus also being suitable for classification of abnormal brain state. The dataset available at: https://www.kaggle.com/datasets/amananandrai/complete-eeg-dataset/data

The EEG Brainwave Dataset (DS2): Feeling Emotions contains multi-channel EEG recordings labeled into three emotional categories: Positive, Neutral, and Negative, derived from subjects exposed to various emotion-evoking stimuli [29]. Each recording is preprocessed to remove noise and artifacts, ensuring high-quality neural signals suitable for deep learning. The dataset typically includes around 2548 total samples, where approximately 70% (1750 samples) are used for training, 39% (758 samples) for are used for testing, with all subsets maintaining balanced representation of the three classes. The structure of the dataset—multi-channel EEG, three clearly defined emotional labels, and artifact-cleaned time-series signals—makes it especially well-suited for the Deep Driven Framework (DDF), which requires rich temporal–spatial patterns to learn adaptive features across brain regions. Moreover, the dataset's emotional variability provides an ideal benchmark for testing DDF's ability to extract fine-grained oscillatory signatures and classify cognitive–affective brain states with high robustness and generalization. The dataset available at https://www.kaggle.com/datasets/birdy654/eeg-brainwave-dataset-feeling-emotions

EEG Motor Movement/Imagery Dataset (DS3): The high-quality EEG recordings of 109 healthy subjects as they performed real and imagined actions in 14 experimental tasks that included left hand, right hand, both hands, both feet movements and a rest state—the resulting dataset has over 1500 well-structured EEG trials. All of the recordings were collected using a 64-channel BCI2000 system, sampled at 160 Hz, according to the international 10–20 electrode placement; all trials in each recording were annotated with well-defined motor imagery classes such as Left Fist Imagery, Right Fist Imagery, Both Feet Imagery and Rest [30]. The balanced annotation plan and clear frequency spectrum of the dataset have potential to be used on a robust multiclass learning pipeline that is commonly partitioned 70–80% for training and 20–30% testing, according to the experimental design. Its complex spatial–temporal progression of activity and multi-channel EEG actions offer solid evidence for deep neural architectures, while DDF in particular stands to gain from this diversity as the dataset affords capability learning of: spatial sensor dependencies, shift of motor imagery signal over time, hierarchy coalescence brainwave characteristics. Together, these properties of the dataset – scale, clear labeling and cognitive–motor variability – render it a very useful and potent resource for training and testing DDF-based EEG classification models in advanced BCI research. The dataset available at: https://physionet.org/content/eegmmidb/1.0.0/

7. RESULTS AND DISCUSSIONS

Table 1: Quantitative performance of Algorithms for DS1

Performance Metrics	Narrow NN Classifier	EEMD [31]	DDF (Proposed)
Precision	82.22%	83.23%	93.12%
Accuracy	96.83%	96.87%	99.34%
Recall	100%	97%	98.78%
Specificity	84.19%	86.12%	98.91%
F1S	92.56%	94.76%	98.11%

Table 2: Quantitative performance of Algorithms for DS2

Performance Metrics	Narrow NN Classifier	EEMD [30]	DDF (Proposed)
Precision	80.11%	84.87%	94.52%
Accuracy	95.83%	94.87%	98.34%
Recall	99%	96%	99.78%
Specificity	83.69%	85.12%	99.91%
F1S	91.91%	95.16%	97.11%

Table 3: Quantitative performance of Algorithms for DS3

Performance Metrics	Narrow NN Classifier	EEMD [30]	DDF (Proposed)
Precision	79.91%	84.23%	94.62%
Accuracy	95.91%	94.87%	99.34%
Recall	98.11%	96%	99.78%
Specificity	85.78%	87.12%	99.91%
F1S	93.75%	95.76%	99.11%

8. CONCLUSION

The proposed DDF represents a strong and unified structure that can be applied to boost the performance of EEG-based brain–computer interface. Approach DDF includes advanced preprocessing, adaptive feature extraction and robust decision framework for improved reliability of EEG interpretation across different conditions. The model accurately identifies emotional states, motor control intentions and cognitive attention levels that illustrate its potential on various BCI application scenarios. Its strong discriminative ability to differentiate happy from angry emotions, left hand versus right hand movement and highly attentive versus lowly attentive states are all evidence for its good discrimination power. In summary, DDF is an adaptable, flexible and scalable methodology that can be applied to next-generation BCI systems for precise real-time decision-making in healthcare, neurotechnology and human–machine interaction devices.

REFERENCES

[1] A. Das, S. Singh, J. Kim, Tariq Ahamed Ahanger, and Anil Audumbar Pise, “Enhanced EEG signal classification in brain computer interfaces using hybrid deep learning models,” Scientific Reports, vol. 15, no. 1, Jul. 2025, doi: https://doi.org/10.1038/s41598-025-07427-2.

[2] I. Hameed, D. M. Khan, S. M. Ahmed, S. S. Aftab, and H. Fazal, “Enhancing motor imagery EEG signal decoding through machine learning: A systematic review of recent progress,” Computers in Biology and Medicine, vol. 185, p. 109534, Dec. 2024, doi: https://doi.org/10.1016/j.compbiomed.2024.109534.

[3] X. Wu, R. Ouyang, and C. Zhang, “Learning-based EEG rhythm analysis for the enhancement of motor imagery-based brain-computer interface performance,” Biomedical Signal Processing and Control, vol. 102, p. 107345, Apr. 2025, doi: https://doi.org/10.1016/j.bspc.2024.107345.

[4] W. Chen, Y. Cai, A. Li, Y. Su, and K. Jiang, "MDD diagnosis based on EEG feature fusion and improved feature selection,” Biomedical Signal Processing and Control, vol. 102, p. 107271, Apr. 2025, doi: https://doi.org/10.1016/j.bspc.2024.107271.

[5] Y. Liao, R. Chen, Z. Li, L. Jie, R. Yan, and M. Li, Personality analysis based on multi-characteristic EEG signals, Biomedical Signal Processing and Control, vol. 102, p. 107369, Apr. 2025, doi: https://doi.org/10.1016/j.bspc.2024.107369.

[6] A. Mohan and R. S. Anand, "Enhanced EEG Signal Spectral Visualization for Imagined Speech Task Prediction," 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kamand, India, 2024, pp. 1-6, doi: 10.1109/ICCCNT61001.2024.10725791.

[7] B. Wu, W. Meng, and W.-Y. Chiu, "Towards Enhanced EEG-based Authentication with Motor Imagery Brain-Computer Interface," Technical University of Denmark, DTU Orbit (Technical University of Denmark, DTU), pp. 799–812, Dec. 2022, doi: https://doi.org/10.1145/3564625.3564656.

[8] S. K. Khare, V. Blanes-Vidal, E. S. Nadimi, and U. R. Acharya, “Emotion recognition and artificial intelligence: A systematic review (2014–2023) and research recommendations,” Information Fusion, vol. 102, p. 102019, Feb. 2024, doi: https://doi.org/10.1016/j.inffus.2023.102019.

[9] K. Kamble and J. Sengupta, “A comprehensive survey on emotion recognition based on electroencephalograph (EEG) signals,” Multimedia Tools and Applications, Feb. 2023, doi: https://doi.org/10.1007/s11042-023-14489-9.

[10] J. Sun, J. Han, Y. Wang and P. Liu, "Memristor-Based Neural Network Circuit of Emotion Congruent Memory With Mental Fatigue and Emotion Inhibition," in IEEE Transactions on Biomedical Circuits and Systems, vol. 15, no. 3, pp. 606-616, June 2021, doi: 10.1109/TBCAS.2021.3090786.

[11] S. S. Jasim and A. K. Abdul Hassan, “Modern drowsiness detection techniques: a review,” International Journal of Electrical and Computer Engineering (IJECE), vol. 12, no. 3, p. 2986, Jun. 2022, doi: https://doi.org/10.11591/ijece.v12i3.pp2986-2995

[12] J. Zhang, Z. Yin, P. Chen, and S. Nichele, “Emotion recognition using multi-modal data and machine learning techniques: A tutorial and review,” Information Fusion, vol. 59, pp. 103–126, Jul. 2020, doi: https://doi.org/10.1016/j.inffus.2020.01.011.

[13] R. R. Adyapady and B. Annappa, “A comprehensive review of facial expression recognition techniques,” Multimedia Systems, Jul. 2022, doi: https://doi.org/10.1007/s00530-022-00984-w.

[14] S. M. Turjya, R. Singh, B. B. Dash, M. K. Gourisaria, S. S. Patra and A. Bandyopadhyay, "EEG Signal-Based Sentiment Analysis for Brain-Computer Interfaces: A Comprehensive Comparison Between Stacking-Ensemble and Deep Learning Approaches," 2024 IEEE 21st India Council International Conference (INDICON), Kharagpur, India, 2024, pp. 1-6, doi: 10.1109/INDICON63790.2024.10958433.

[15] M. Liu, W. Guo, J. Chen, B. Zhang and Y. Wang, "Enhancing EEG Signals Classification through Spatio-Temporal Feature Fusion in Dense Connection Neural Networks," 2024 IEEE 17th International Conference on Signal Processing (ICSP), Suzhou, China, 2024, pp. 577-581, doi: 10.1109/ICSP62129.2024.10846701.

[16] Shakeela Banu C; Imtiyaz Ahmed B K; Awakash Mishra; Ashish Verma; Asit Kumar Subudhi; Manish Nagpal, "Improving EEG Signal Classification with Recurrent Neural Networks for Brain-Computer Interfaces," 2025 International Conference on Networks and Cryptology (NETCRYPT), New Delhi,

India, 2025, pp. 1080-1085, doi: 10.1109/NETCRYPT65877.2025.11102287.

[17] A. Mohan and R. S. Anand, "Phase-Based EEG Analysis for Enhanced Imagined Speech Decoding in Brain-Computer Interfaces," 2025 International Conference on Cognitive Computing in Engineering, Communications, Sciences and Biomedical Health Informatics (IC3ECSBHI), Greater Noida, India, 2025, pp. 1-6, doi: 10.1109/IC3ECSBHI63591.2025.10990955.

[18] S. Hana, R. Hassan, A. R. Faizabadi, A. Gubbi, M. Z. Bellary and A. B. M, "Leveraging EEG and Signal-to-Noise Ratio Augmentation for Advanced Stress Detection," 2025 4th International Conference on Distributed Computing and Electrical Circuits and Electronics (ICDCECE), Ballari, India, 2025, pp. 1-7, doi: 10.1109/ICDCECE65353.2025.11035392.

[19] X. Huang, L. Wang, L. Ren and Q. Zhan, "EEG Signals Recognition of Active Brain-Computer Interface Based on Sequential Encoding," 2022 7th International Conference on Intelligent Computing and Signal Processing (ICSP), Xi'an, China, 2022, pp. 1821-1826, doi: 10.1109/ICSP54964.2022.9778599.

[20] R. Raman, V. Kumar, C. P. Sanjay, A. Verma, S. Rastogi and D. Pandey, "Advancing EEG Brain-Computer Interfaces with Efficient Machine Learning Classifications," 2024 Asian Conference on Intelligent Technologies (ACOIT), KOLAR, India, 2024, pp. 1-5, doi: 10.1109/ACOIT62457.2024.10939133.

[21] H. E. M. Abdalla, S. A. R. Al-Haddad, H. B. Basri, I. B. Aris, A. H. K. B. Yusofv and H. Neyaz, "Brain-Computer Interface System Based on Common Spatial Patterns for Inner Speech Recognition from Electroencephalography Signal by Using a Convolutional Neural Networks," 2024 IEEE International Conference on Systems, Man, and Cybernetics (SMC), Kuching, Malaysia, 2024, pp. 2021-2027, doi: 10.1109/SMC54092.2024.10831764.

[22] A. Pant and A. Kumar, "EEG Signal Filtering Using Rectangular FIR Window Method," 2024 International Conference on Computer, Electronics, Electrical Engineering & their Applications (IC2E3), Srinagar Garhwal, Uttarakhand, India, 2024, pp. 1-7, doi: 10.1109/IC2E362166.2024.10827368.

[23] A. Pant, A. Kumar, C. Verma, and Z. Illés, “Comparative exploration on EEG signal filtering using window control methods,” Results in Control and Optimization, vol. 17, p. 100485, Dec. 2024, doi: https://doi.org/10.1016/j.rico.2024.100485.

[24] C. Hu, K. Wang, J. Cai, Y. Zhang, Z. Liang and W. Chen, "An Adaptive Common Spatial Pattern for EEG Signal Classification in Different Channel," 2022 IEEE 17th Conference on Industrial Electronics and Applications (ICIEA), Chengdu, China, 2022, pp. 961-966, doi: 10.1109/ICIEA54703.2022.10006026.

[25] C. Thorp, S. Sisti and W. Bennette, "Feature Extraction for Out of Distribution Detection via Self-Supervised Learning," 2022 21st IEEE International Conference on Machine Learning and Applications (ICMLA), Nassau, Bahamas, 2022, pp. 920-924, doi: 10.1109/ICMLA55696.2022.00153.

[26] Xiong, X., Wang, Y., Song, T., Huang, J., & Kang, G. (2023). Improved motor imagery classification using adaptive spatial filters based on particle swarm optimization algorithm. Frontiers in neuroscience, 17, 1303648. https://doi.org/10.3389/fnins.2023.1303648

[27] X. Xiong, Y. Wang, T. Song, J. Huang, and G. Kang, “Improved motor imagery classification using adaptive spatial filters based on particle swarm optimization algorithm,” Frontiers in Neuroscience, vol. 17, Dec. 2023, doi: https://doi.org/10.3389/fnins.2023.1303648.

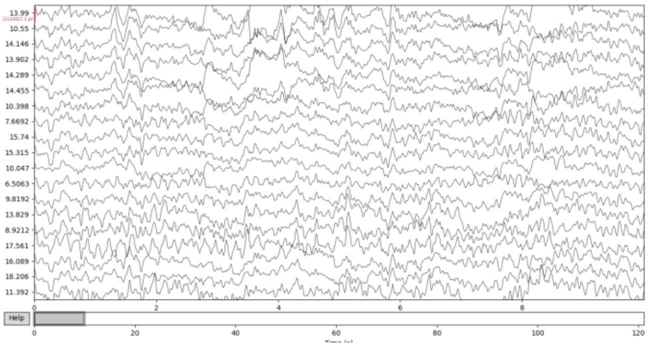
[28] J. J. Bird, A. Ekart, C. D. Buckingham, and D. R. Faria, “Mental emotional sentiment classification with an eeg-based brain-machine interface,” in The International Conference on Digital Image and Signal Processing (DISP’19), Springer, 2019.

[29] K. Golder, A. Nag, F. F. Tarun, H. Mondal, M. M. Hassan and A. Karim, "EmotionRF: Enhancing Emotion Classification from EEG Signals Using Machine Learning with Explainable AI," 2024 27th International Conference on Computer and Information Technology (ICCIT), Cox's Bazar, Bangladesh, 2024, pp. 19-24, doi: 10.1109/ICCIT64611.2024.11021975.

[30] G. Schalk, D. J. McFarland, T. Hinterberger, N. Birbaumer, and J. R. Wolpaw, “EEG Motor Movement/Imagery Dataset,” PhysioNet, Jan. 2004, doi: https://doi.org/10.13026/c28g6p.

[31] V. S. Kardam, S. Taran, and A. Pandey, “Motor Imagery Tasks Based Electroencephalogram Signals Classification Using Data-Driven Features,” Neuroscience Informatics, vol. 3, no. 2, p. 100128, Jun. 2023, doi: https://doi.org/10.1016/j.neuri.2023.100128.

Figure:



Dataset:

Table 1: Quantitative performance of Algorithms for DS1

Performance Metrics	Narrow NN Classifier	EEMD [31]	DDF (Proposed)
Precision	82.22%	83.23%	93.12%
Accuracy	96.83%	96.87%	99.34%
Recall	100%	97%	98.78%
Specificity	84.19%	86.12%	98.91%
F1S	92.56%	94.76%	98.11%

Table 2: Quantitative performance of Algorithms for DS2

Performance Metrics	Narrow NN Classifier	EEMD [30]	DDF (Proposed)
Precision	80.11%	84.87%	94.52%
Accuracy	95.83%	94.87%	98.34%
Recall	99%	96%	99.78%
Specificity	83.69%	85.12%	99.91%
F1S	91.91%	95.16%	97.11%

Table 3: Quantitative performance of Algorithms for DS3

Performance Metrics	Narrow NN Classifier	EEMD [30]	DDF (Proposed)
Precision	79.91%	84.23%	94.62%
Accuracy	95.91%	94.87%	99.34%
Recall	98.11%	96%	99.78%
Specificity	85.78%	87.12%	99.91%
F1S	93.75%	95.76%	99.11%

Subject
Manuscript Submission: **Deep Driven Framework for Enhanced EEG-Based Brain-Computer Interfaces**

Dear Editor,

We are pleased to submit our manuscript entitled **"A Deep Driven Framework for Enhanced EEG Signal Interpretation in Brain Computer Interfaces"** for consideration for publication in your esteemed journal.

This manuscript presents a novel Deep Driven Framework (DDF) designed to improve EEG signal classification accuracy across multiple BCI applications, including cognitive workload detection, emotion recognition, and motor imagery classification. Unlike conventional machine learning approaches, the proposed DDF integrates adaptive preprocessing, spatial–temporal feature encoding, attention-based deep learning layers, and a robust discriminative decision module within a unified end-to-end architecture.

This work has not been published previously and is not under consideration elsewhere. All authors have approved the manuscript and agree with its submission. We believe the findings will be valuable to researchers and practitioners working in neurotechnology, biomedical signal processing, and intelligent BCI systems and do the needful.

Sincerely,

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