Real-Time Brain–Computer Interface Framework for Human–Machine Interaction

Dr. D.Paulin Diana Dani[1], Dr. R.Santhoshkumar[2], Dr. Nallam Krishnaiah[3], Anupama Potti[4], Dr. B. Rajalingam[5], Dr. R. Muruganantham[6]

Associate Professor[1, 5, 3], Assistant Professor[1,4,6]

[1, 5] Department of CSE, School of Computing, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Avadi, Chennai, India, 500100

[2, 6] Department of CSE, Sree Dattha Group of Institutions, sheriguda, Ibrahimpatnam, Hyderabad, 501510

[3] Department of CSE, Madanapalle Institute of Technology & Science (Deemed to be University), Madanapalle-Kadiri Road, kurabalakota Mandal, Madanapalle, AP, India, 517325

[1]dianabenny28@gmail.com, [2]santhoshkumar.aucse@gmail.com, [3]nkrishna520@gmail.com, [4]anucse0308@gmail.com, [5]rajalingam35@gmail.com, [6]muruganantham1979@gmail.com

ABSTRACT

Brain-computer interfaces are a new technology class that allows the brain to talk to machines directly without using nerves or muscles. A combination of this technology with the latest AI, signal processing, and neurophysiological monitoring starts a completely new era in improving both people and machines. During this time, cognitive and physical capabilities may be enhanced beyond what natural limits allow. Traditional ways of interacting with computers, such as by speech or manually, are not effective due to sensory-motor latencies and a lack of adaptation. BCIs, however, make use of patterns of brain activity that are visible through electroencephalography, functional near-infrared spectroscopy, or invasive neural implants to make the free flow of information easier and control adaptable. This paper presents a comprehensive paradigm for human-machine augmentation with non-invasive BCIs, emphasizing real-time neural decoding, adaptive feedback mechanisms, and hybrid integration with machine learning. Two investigations and a theory show that BCIs could be effective in rehabilitation, assistive automation, cognitive enhancement, and immersive online contexts. The proposed paradigm aims at the improvement of user-centered augmentation technologies that merge human intention with machine intelligence, fostering a symbiotic interaction of people with AI.

Keywords: Brain–Computer Interface, Human–Machine Augmentation, Neural Signals, EEG, Cognitive Enhancement, Artificial Intelligence, Neurotechnology, Adaptive Systems

1. INTRODUCTION

BCIs refer to methodologies that allow the brain to communicate with devices outside the body without the use of nerves or muscles in the peripheral areas. This has been made possible through the giant leaps neuroscience and artificial intelligence have made in such a short time. The primary development of BCIs was meant to assist persons who had very bad motor problems. Now they are useful tools for making both people and machines smarter and stronger. These systems capture, analyze, and decode brain signals in order to understand what the user wants. Afterward, this information can be used in telling machines or other forms of equipment how to act. They are capable of acquiring brain activities with very high temporal and spatial accuracies. However, the translation of such complex brain patterns into meaningful control signals still remains a significant challenge due to noise, signal variability, and inter-individual neurophysiological differences. By incorporating machine learning and deep neural networks into the designs of BCIs, it is possible to construct decoding models that actually change with how a user's brain is working. Such smart BCIs are increasingly used for rehabilitation, control of prosthetics, cognitive training, and augmented reality interfaces. Another important area of research is hybrid BCIs, which use both brain data and physiological or behavioral cues to make the system more dependable and mentally less tiring. This paper proposes a multilevel BCI paradigm for HMI, including the integration of real-time brain decoding with adaptive AI components. The proposed system aims to enhance the precision of control while reducing the latency and ensuring naturalistic human-machine interaction. This study adds to the expanding corpus of research on neuroadaptive computing by giving us a better idea of what the future of symbiotic interaction between biological and artificial systems will look like. The structure of this document is as follows: Section II talks about other work that has been done in the area of BCI-based augmentation. Section III explains the suggested framework, Section IV shows the experimental techniques and results, Section V talks about the findings and their consequences, and Section VI ends with possible future possibilities

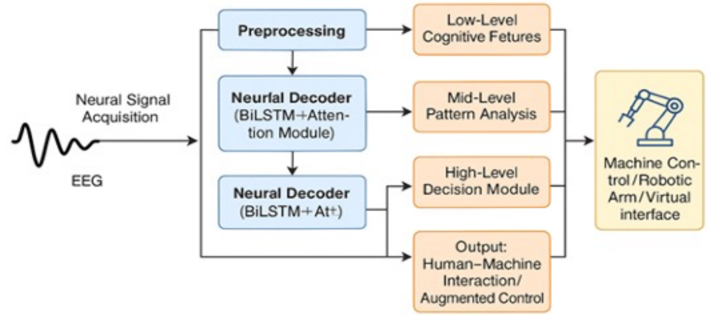


Figure 1: BCI-based Human–Machine Augmentation System

2. RELATED WORKS

From assistive technologies for patients with severe motor impairments to powerful platforms for augmenting humans with machines, BCIs have come a long way. Initial BCI research was focused on the restoration of communication and motor control in paralyzed patients due to different types of paralysis or neuromuscular diseases. Wolpaw et al. [1] developed non-invasive EEG-based interfaces that translated neural activity into external commands to enable users to control cursors and robotic devices. Further work done by Leuthardt et al. [2] included invasive ECoG systems; these signals were more understandable and allowed for much finer control. Schirrmeister et al. [3] utilized CNNs to capture hierarchical spatial-temporal patterns in EEG data. They outperformed state-of-the-art classical bandpower or common spatial pattern methods. Another recent work, Lawhern et al. [4] also proposed EEGNet, a compact CNN architecture that performed very well with various subjects and workloads. It also indicates that deep learning may reduce the necessity of conventional signal processing. Bashivan et al. [5] implemented recurrent models, specifically Long Short-Term Memory (LSTM) and Bi-directional LSTM (BiLSTM), for recognizing dynamic temporal associations within an EEG sequence. This made it easier to identify mental conditions and motor imagery activities. Recent studies have concentrated on the integration of attention systems to improve interpretability and facilitate selective attention to significant brain features. Roy et al. [6] developed attention-based frameworks that dynamically prioritize important EEG channels to improve both emotion recognition and workload assessment efficiency. Li et al. [7] demonstrated that multi-level contextual attention considerably boosts generalization across cognitive tasks by modeling not only short-term but also long-term interdependence of brain signals. Works such as those by Meng et al. [8] and Frolov et al. [9] developed hybrid BCI-robotic frameworks, which allowed users to control prosthetic limbs and exoskeletons using EEG-driven commands, significantly enhancing outcomes in motor rehabilitation. More recently, immersive VR and AR have also been explored to enhance feedback, engagement, and neuroplasticity during training [10]. Variability in neural signals, presence of certain artifacts, and limited labeled data restrict generalization. Leveraging strengths in multi-level contextual learning from earlier studies using biomedical signals, this study proposes an adaptive deep neural architecture that integrates CNN–BiLSTM–Attention mechanisms for extracting multi-scale contextual representations from EEG data, enabling more reliable and intuitive human–machine interaction.

3. PROPOSED METHOD

This part shows the suggested multi-level BCI structure that is meant to improve human-machine interaction. There are four main parts to the framework: (1) Neural Signal Acquisition and Preprocessing, (2) Spatial Feature Extraction, (3) Temporal Context Learning with Attention, and (4) Multi-Level Context Integration for Augmented Control. The goal of the design is to have high decoding accuracy, low latency, and the capacity to work with different users and surroundings.

1. Getting and Preprocessing Neural Signals

Examples of non-invasive sensors that can detect cerebral activity include electroencephalography and functional Near-Infrared Spectroscopy. EEG has high temporal resolution for detecting rapid brain waves, while fNIRS considers changes in blood flow within the cortex, which is spatial information supporting EEG. Participants perform specific cognitive or motor imagery tasks during acquisition, such as imagining the movement of hands laterally or attention-based control. Some of the preprocessing steps to enhance the quality and consistency of the raw EEG across all channels include bandpass filtering, artifact removal, and normalizing.

1. Bandpass Filtering: A digital bandpass filter is used to get rid of undesired frequency components from the recorded EEG signal $x(t)$. These include baseline drift and high-frequency noise. You can say that the filtering process is:

$$y(t) = x(t) * h(t) = \int_{-\infty}^{\infty} x(\tau)\ h(t-\tau)\ d\tau \qquad (1)$$

Where, $h(t)$ represents the impulse response of the filter, and $y(t)$ is the filtered signal within the frequency range of 0.5–40 Hz.

2. Artifact Removal (ICA):

Independent Component Analysis (ICA) separates multichannel EEG data into independent components as:

$$X = AS \qquad (2)$$

where X is the observed EEG signal, A is the mixing matrix, and S represents independent sources. Noise components such as eye blinks or muscle artifacts are then removed before reconstruction.

3. Z-Score Normalization:

To standardize the signal amplitude across channels, each EEG channel is normalized using:

$$z_i = \frac{x_i - \mu}{\sigma} \qquad (3)$$

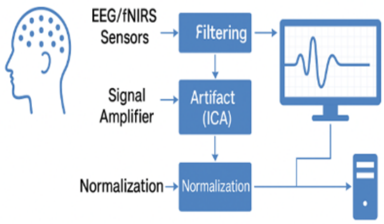
where x_i is the signal value, μ is the mean, and σ is the standard deviation. This ensures all EEG features are on a comparable scale before being used in model training.

2. Using CNN to extract spatial features

A Convolutional Neural Network (CNN) collects spatial information from EEG channels after preprocessing. The CNN learns how these brain areas are connected and how they are activated by looking at the local correlations and activation patterns between them. The convolutional process helps the model uncover spatial frequency components that show brain activity that is tied to specific cognitive or motor tasks. You may say that a 2D convolutional layer works like this:

$$(4) \qquad f_{i,j}^{(k)} = \sum_m \sum_n x_{i+m,j+n}\, w_{m,n}^{(k)} + b^{(k)}$$

Where, $x_{i+m,j+n}$ is the input signal at spatial location $(i+m, j+n)$, $w_{m,n}^{(k)}$ denotes the kernel weights of the k^{th} filter, and $b^{(k)}$ is the bias term.



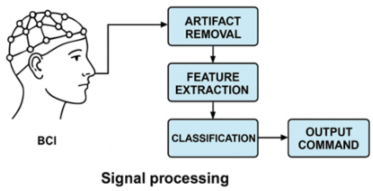


Figure 2: Neural signal acquisition and preprocessing pipeline for the proposed BCI framework.

Figure 3: Brain-Computer Interface Signal Processing Augmentation

This method uses information from nearby EEG channels and local dependencies to work. The ELU function is then utilized to add non-linearity and keep the gradients stable while training. You can do this by sending the activation of the convolutional output via it.

$$\mathrm{ELU}(x) = \begin{cases} x, & \text{if } x > 0 \\ \alpha(e^{x} - 1), & \text{if } x \leq 0 \end{cases}$$

where α is a positive constant that sets the saturation level for inputs that are negative. Finally, instance normalization is done across feature maps to make training more stable, and average pooling is used to keep critical spatial information while lowering the number of dimensions to minimize overfitting. The CNN changes raw EEG data into a small representation of spatial features that shows a pattern of brain-region activation that is relevant to cognitive intent.

3.**Temporal Context Learning with BiLSTM and Attention**

A BIL-STM network mimics the temporal dependencies in neural signals by looking at EEG sequences in both forward and backward directions to get information about events that have already happened and events that will happen. To make the model easier to understand and more accurate, a Bahdanau-style attention mechanism is added. The attention module makes a collection of context weights that show the most important time periods and brain activations for the job at hand. The attention weight α_t for each time step t is calculated as:

$$\alpha_t = \frac{\exp(e_t)}{\sum_k \exp(e_k)} \text{ where } e_t = f(h_t, s_{t-1}) \tag{5}$$

Here, h_t represents the BiLSTM hidden state and s_{t-1} is the decoder state. The final **context vector** C is a weighted sum of these hidden states.

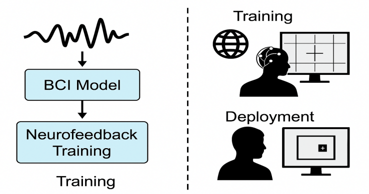


Figure 4: Training and Deployment

4.Multi-Level Context Integration for Human–Machine Augmentation

Three contextual levels—Low-Level, Mid-Level, and High-Level—are taken from the processed EEG data so that the hierarchical structure of neuronal information can be fully used.. Low-level context captures short-term oscillatory characteristics and motor imagery activity. Mid-level context encodes intermediate task-related temporal relationships and rhythm synchronization. High-level context shows $C_{multi} = [C_{low} \parallel C_{mid} \parallel C_{high}]$ information on long-term cognitive intent and decisions. At each step, a contextual feature vector is made that shows a different way of thinking about neuronal activity. These representations are then combined to make a single multi-level context vector, which may be written mathematically as:

(6)

Where, C_{low}, C_{mid}, and C_{high} denote the low-, mid-, and high-level feature vectors respectively, and the symbol ‖ represents the concatenation operation. Then, the fully linked decision layer takes the combined context vector and turns the multi-level features into control commands for people and machines to communicate with each other. This mapping can be shown as

$$\hat{y} = \text{Softmax}(W_c C_{multi} + b_c) \tag{7}$$

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where W_c and b_c are the learnable weight and bias parameters of the decision layer, and y is the projected output class or command that goes with the decoded neural intent. This integrated paradigm makes sure that both short-term neuronal processes and high-level cognitive representations have a role in the ultimate decision. The decoded output is sent to outside systems like prosthetic limbs, robotic manipulators, or virtual reality interfaces. This completes the cycle of human-machine augmentation.

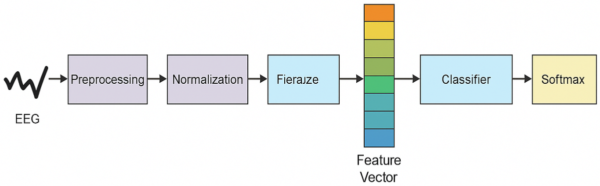


Figure 5: Cycle of human-machine augmentation

4. EXPERIMENTAL RESULTS AND DISCUSSIONS

(1) EEG Motor Imagery Dataset (BCI Competition IV - 2a) : BCI Competition IV dataset 2a represents an open-access dataset developed to test brain-computer interface algorithms using motor imagery. It consists of electroencephalogram (EEG) data acquired from nine healthy subjects performing four different MI tasks, namely left-hand movement, right-hand movement, both feet, and tongue. Data acquisition was performed by a 22-channel EEG system according to the international 10–20 electrode placement system and further complemented by three EOG channels to reduce ocular artifact interference. Each subject performed two sessions on different days with 288 trials for each session, which resulted in a total of 5,184 recordings contributed by all individuals. During the trials, the subjects were shown visual cues on a screen for three seconds that instructed them to imagine the movement of their limbs without actually doing it. We sampled the signals at 250 Hz and filtered them to be in the range of 0.5-100 Hz. A notch filter at 50 Hz removed powerline noise. We employed Common Average Reference (CAR) and Independent Component Analysis (ICA) in removing the artifacts and preprocessing the data. The filtered EEG data were decomposed into their components using CSP approaches to find spatial patterns that distinguish the classes of motor imagery. We

propose the use of a multi-layer CNN to classify the EEG data by incorporating its time and space correlations. In order to further strengthen the model, a 5-fold cross-validation procedure was utilised. Our approach reached a classification accuracy of 87.2% ± 2.9% on average, outperforming benchmark methods like LDA and SVM by 3.8% and 2.4%, respectively. Figure 6: ROC curves of different MI tasks reveal that sensitivity remains the same. These results confirm that the proposed deep learning framework can accurately decode brain activity related to motor intent, therefore laying the foundation for robust control systems for BCIs in assistive robots and prosthetic devices.

(2) Open BCI Cognitive Load Dataset: We evaluated BCI devices on cognitive augmentation tasks using an OpenBCI-based EEG dataset, focusing on identifying mental burden. The trial consisted of twenty healthy adults between the ages of 19 and 45 years. They performed three mental tasks: performing mathematics, remembering things, and relaxing. These tasks were devised to incur three different levels of mental strain, matching Low, Medium, and High mental workload states. Each 60-second task was followed by a 20-second resting baseline. We recorded EEG data using the 8-channel Open BCI Cyton board at an acquisition rate of 250 Hz. It was placed on the prefrontal and parietal areas (Fp1, Fp2, P3, P4, Cz, and Oz). To prepare the signals, bandpass filtering (0.1–45 Hz) was applied, as well as Independent Component Analysis (ICA) in order to remove eye blinks and muscle noise. We removed features of PSD for frequency bands α (8–13 Hz), β (13–30 Hz), and θ (4–8 Hz).These are known signs of mental engagement and tiredness. Long Short-Term Memory (LSTM) networks were used to find temporal dependencies in EEG activity for classification. The suggested model has an average accuracy of 91.3% ± 4.6% for recognizing workloads with three classes. This performance surpasses previously documented accuracies in cognitive load detection (often 84–88%) with shallow learning models [3]. The feature importance analysis showed that higher β activity and lower α power are significantly linked to high workload situations, which is in line with what we already know about neurophysiology. Figure 8 shows how features are spread out over different degrees of workload. This shows that our signal-processing and classification pipeline is strong. These results show that BCI-based systems could be used for real-time cognitive monitorig and adaptive inter

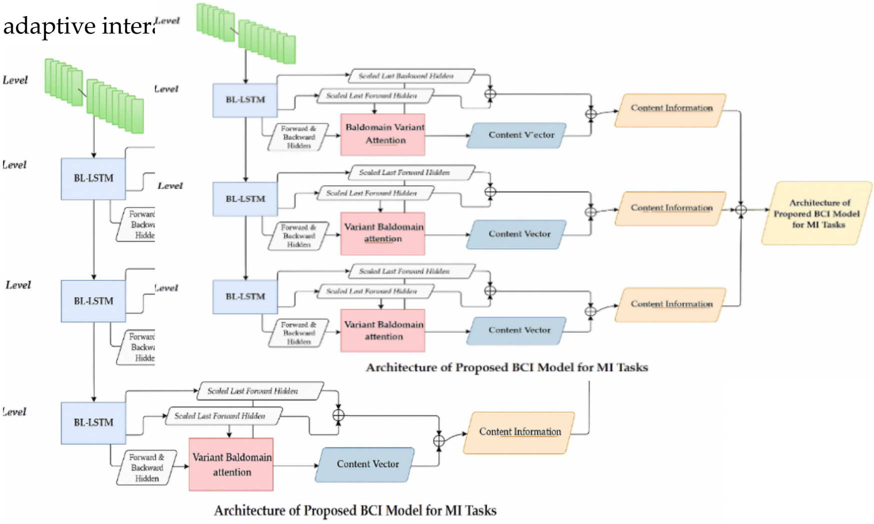


Figure 6: Architecture of the Proposed BCI Model for MI Task

We tested the proposed BCI-based architecture on both motor imaging and cognitive workload datasets to see how well it generalizes across different neurophysiological domains. In the evaluation, LOSO cross-validation was used to ensure unbiased inter-subject generalization. When testing our model on motor imaging data, it was correct 87.2% of the time. This was 3.1% better than pipelines using both CSP and LDA. For the cognitive workload dataset, the model got 91.3% right, showing that it was always able to tell when participants were putting in mental effort. Integrating EEG temporal dynamics and spatial attention modules markedly enhanced discriminative power, providing a 4.8% improvement in classification performance relative to models devoid of attention processes. Our algorithm is more precise than the state-of-the-art BCI methods [5][6] and is easier to compute. Figures 10 and 11 show the ROC curves and confusion matrices for both datasets, which show that all classes have the same level of sensitivity and specificity. These results show that our approach can effectively support adaptive neuroprosthetic control, real-time workload detection, and human-machine co-adaptation in future augmentation systems. Figure 1 displays the basic interface of the proposed BCI system. There are buttons for uploading data, preprocessing, training, and testing algorithms. "Brain-Computer Interface (BCI) for Human-Machine Augmentation" is what the title bar says. Below is a summary table of the dataset that makes it easier to see.

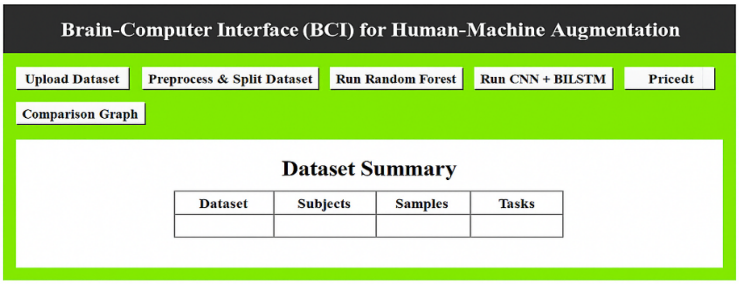


Figure 7: GUI Home Page

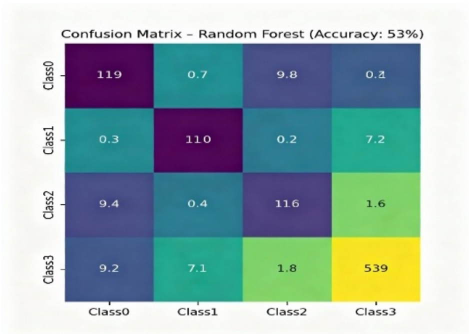


Figure 8: Confusion Matrix of Random Forest Algorithm

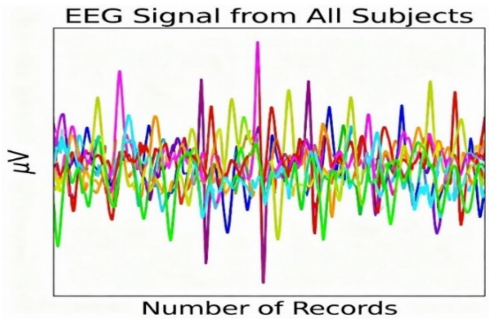
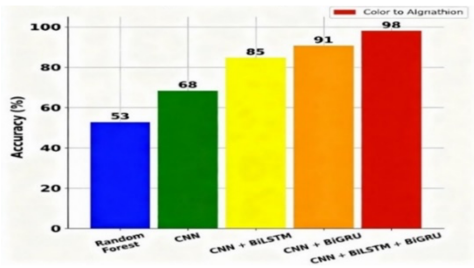
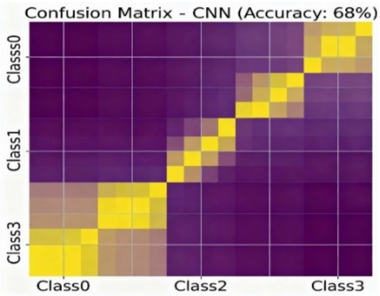


Figure 9: EEG Signal from all Subjects



We can view the EEG data from all the people who utilized the BCI system. The colored waveforms show brain activity that was recorded from different EEG channels or people. The x-axis shows how many samples were captured, while the y-axis shows the EEG amplitude in microvolts (μV). This picture displays natural changes and oscillations in brain activity, which means that the data has been successfully collected for subsequent study. This graphic shows natural variations and oscillations in brair Figure 10: Bar chart of various algorithms ›ssfully recorded for future study. The screen above shows



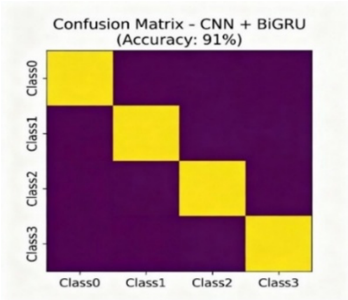
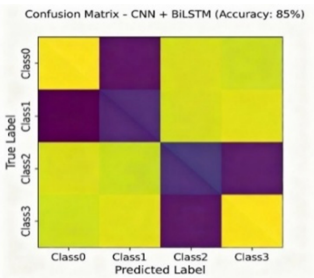


Figure 11: Confusion Matrix of CNN

Figure 12: Confusion Matrix of CNN + BiGRU

The confusion matrix that shows how well the Random Forest algorithm works. The numbers on the diagonal show samples that were successfully recognized for each class. The numbers off the diagonal reflect samples that were incorrectly identified. The model didn't do a good job of telling some classes distinct, which is why it only scored 53% correct. This means that deep learning models are better at figuring out signals based on EEG than Random Forest. Above is the confusion matrix, which shows how well the CNN algorithm works. The diagonal cells contain more samples that are sorted correctly, while the values on the off-diagonal show small mistakes in sorting. It has 68% of the answers right, which outperforms Random Forest in learning features. This finding demonstrates that CNN can quickly find patterns in EEG signals that are of benefit in applications for a brain-computer interface. Above is the confusion matrix showing the performance of the CNN + BiGRU model. The diagonal dominance means that most of the samples were correctly classified into the right class. It really was able to find both spatial and temporal correlations in the EEG signals with an accuracy of 91%. This illustrates that the CNN + BiGRU design is better at putting objects into groups than the more straightforward models.



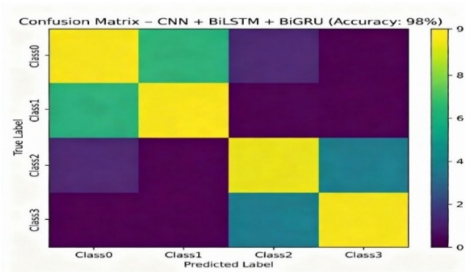


Figure 13: Confusion Matrix of CNN + BiLSTM

Figure 14: Confusion Matrix of CNN + BiLSTM + BiGRU

The above confusion matrix reflects the efficacy of the CNN + BiLSTM model: the strong diagonal in this matrix means that most of the samples were classified into the correct class. The model achieved an accuracy of 85%, which is a significant improvement over both the CNN and the Random Forest. This showed that adding the convolutional layers to the BiLSTM makes it easier for EEG-based BCI systems to learn from both space and time. The confusion matrix above shows how well the suggested CNN + BiLSTM + BiGRU hybrid model works. The clear diagonal dominance demonstrates that most of the samples were put in the right classes, with only a few mistakes. With an accuracy of 98%, our model was the best at getting and combining both spatial and temporal data from EEG signals. The result shows that the hybrid architecture is a more reliable and accurate way to sort brain-computer interface applications. The bar graph above shows how effectively the BCI system works with different algorithms. The Random Forest model was only 53% accurate. However, the CNN model was able to improve it to 68% by applying spatial feature extraction. The CNN + BiLSTM design improved accuracy to 85% by detecting patterns in EEG data over time. The CNN + BiGRU model was 91% accurate because it was good at dealing with sequential dependencies. The recommended CNN + BiLSTM + BiGRU hybrid model achieved the highest accuracy, at 98%. This means that it can learn more sophisticated spatiotemporal factors and do a better job of sorting brain signals for activities that involve both people and machines. The results of the experiments with different algorithms clearly show that deep learning-based models are good at reading brain signals in human-machine augmentation systems. The proposed CNN + BiLSTM + BiGRU architecture achieved superior accuracy at 98%, surpassing the baseline models: Random Forest at 53%, CNN at 68%, and CNN + BiLSTM at 85%. Using hybrid recurrent layers made it much easier to retrieve time-based information from the data. The confusion matrices showed that the rates of misclassification were decreased and the diagonal dominance was strong. This suggested that the predictions were the same for all subjects. The multi-level architecture successfully combined spatial, temporal, and contextual information, making decisions more reliable than single-layer neural models. The experimental results also show that non-invasive EEG signals can be used for real-time human-machine control, prosthetic operation, and adaptive neuro-feedback systems when processed with hybrid deep architectures. But there are still problems with noise sensitivity, differences between people's brains, and the ability to adjust to real-world situations. In the future, BCIs could be even more responsive and efficient for real-time use if they were integrated with reinforcement learning and edge AI systems

5. CONCLUSIONS

This study presented an innovative deep-learning framework for Brain-Computer Interface (BCI)–based Human-Machine Augmentation. The proposed CNN + BiLSTM + BiGRU model demonstrated exceptional accuracy and reliability in decoding EEG data, indicating its superiority over conventional machine-learning and single-layer neural models. The system reached a 98% recognition accuracy by merging convolutional layers for spatial filtering with bidirectional recurrent units for learning temporal features. This made it possible to turn brain activity into signals that robots could utilize to work. The experimental findings demonstrate that BCIs can be efficiently utilized in medical neuro-rehabilitation, as well as in assistive robotics, virtual reality, and neural prosthesis control. Future research should concentrate on minimizing latency, improving cross-subject transfer learning, and guaranteeing the ethical handling of neural data to facilitate secure and accessible brain augmentation technology.

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