



BCI Performance Optimization Using EEG Band Power and Hybrid Deep Learning

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Abstract: Brain-Computer Interface (BCI) systems rely on accurate interpretation of electroencephalogram (EEG) signals to understand human cognitive states. However, EEG signals are highly noisy, non-linear, and vary across individuals, which reduces classification accuracy. This paper proposes a real-time BCI performance optimization system using EEG band power features and a hybrid deep learning model. The system processes Alpha, Beta, and Gamma brainwave components to extract meaningful band power features. Additionally, EEG signals are converted into spectrogram images to capture time-frequency patterns. A hybrid Convolutional Neural Network (CNN) model is used to combine spectrogram-based image features with numerical band power features for improved classification. The system predicts cognitive states such as Relaxed, Normal, and High Stress. A real-time interactive dashboard is developed for visualization, prediction, and report generation. Experimental results demonstrate improved classification accuracy and robustness compared to traditional approaches. The proposed system enhances BCI reliability and can be applied in healthcare, mental monitoring, and neuro-adaptive systems.

Keywords: EEG, BCI, Deep Learning, CNN, Band Power, Spectrogram, Stress Detection, Neurotechnology

1 INTRODUCTION

Brain-Computer Interface (BCI) systems represent an emerging field that enables direct interaction between the human brain and external devices without the need for muscular activity. These systems rely on electroencephalogram (EEG) signals, which measure electrical activity generated by neurons in the brain. EEG-based BCI systems have found applications in various domains, including healthcare, rehabilitation, gaming, mental state monitoring, and assistive technologies for physically impaired individuals.

Despite their potential, EEG signals present several challenges for accurate analysis and classification. EEG signals are characterized by low signal-to-noise ratio, high variability across subjects, and sensitivity to external artifacts such as eye movements and muscle activity. These characteristics make it difficult to extract meaningful features and achieve reliable classification of cognitive states.

EEG signals are typically divided into different frequency bands, each associated with specific brain activities. Alpha waves (8–12 Hz) are linked to relaxation and calmness, Beta waves (13–30 Hz) are associated with active thinking and stress, and Gamma waves (>30 Hz) are related to higher cognitive processing. The distribution of energy across these bands provides valuable insights into mental states.

Traditional approaches for EEG classification rely on statistical feature extraction methods combined with machine learning algorithms such as Support Vector Machines (SVM) and Random Forest classifiers. While these methods provide moderate accuracy, they often fail to capture complex temporal and frequency relationships present in EEG signals.

Recent advancements in deep learning have introduced powerful models such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), which are capable of automatically learning hierarchical features from raw data. CNNs, in particular, are effective in processing image-like representations such as spectrograms, which convert EEG signals into time-frequency domain.

However, most existing systems rely either on numerical features or image-based representations independently. This limits the overall performance and robustness of BCI systems.



Motivated by these challenges, this paper proposes a hybrid deep learning approach that integrates EEG band power features with spectrogram-based representations. By combining physiological signal features with deep learning capabilities, the proposed system enhances classification accuracy and robustness. Additionally, the system is implemented as a real-time application with an interactive interface, enabling practical deployment and usability.

The rest of the paper is organized as follows. Section 2 presents the related work on EEG-based BCI systems and deep learning approaches. Section 3 describes the system architecture and overall framework. Section 4 explains the mathematical modeling of EEG signal processing. Section 5 details the proposed hybrid deep learning model. Section 6 discusses the experimental setup and evaluation framework. Section 7 presents results and analysis. Finally, Section 8 concludes the paper and outlines future research directions.

2 RELATED WORK

EEG-based BCI systems have been extensively studied over the past decades, with significant advancements in signal processing and machine learning techniques. Early research focused on extracting handcrafted features such as mean amplitude, power spectral density, and statistical measures, followed by classification using traditional machine learning algorithms such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Decision Trees.

While these approaches provided a foundation for EEG analysis, they often struggled with generalization and robustness due to the non-linear and dynamic nature of EEG signals. Additionally, handcrafted features may fail to capture hidden patterns present in the data.

Recent studies have explored the use of deep learning models for EEG classification. Convolutional Neural Networks (CNN) have been widely used for processing spectrogram images derived from EEG signals. These models can automatically learn spatial and frequency-based features, improving classification performance.

Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks have also been applied to EEG data to capture temporal dependencies. However, these models require large datasets and are computationally intensive, making real-time implementation challenging.

Spectrogram-based EEG analysis has gained popularity due to its ability to represent signals in both time and frequency domains. However, relying solely on spectrogram images may ignore important physiological features such as band power distribution.

Hybrid approaches combining multiple feature types have shown promise but are still limited in literature. Moreover, most existing systems lack real-time deployment capabilities.

The proposed system addresses these limitations by integrating band power features with CNN-based spectrogram analysis in a unified hybrid model, while also providing real-time visualization and prediction capabilities.

3 SYSTEM ARCHITECTURE

The proposed BCI system is designed as a multi-stage pipeline that integrates EEG signal processing, feature extraction, deep learning, and real-time visualization. The architecture is structured to efficiently process EEG band values and convert them into meaningful cognitive state predictions.

The overall system consists of the following major components:

3.1 Input Layer

The system accepts EEG band values as input, specifically:

- Alpha (8–12 Hz)
- Beta (13–30 Hz)
- Gamma (>30 Hz)

These values represent the relative activity levels of different brainwave frequencies. In this work, synthetic EEG signals are generated based on these band values to simulate real-time brain activity.

3.2 Signal Generation Layer

The signal generation module creates a continuous EEG waveform using a combination of sine waves corresponding to Alpha, Beta, and Gamma frequencies. Noise components are also introduced to simulate realistic EEG behavior.



This stage ensures that the system can operate even without real EEG hardware, making it suitable for simulation and development purposes.

3.3 Feature Extraction Layer

This layer performs two key operations:

(a) Band Power Calculation

Band power represents the energy of EEG signals within specific frequency ranges. The system computes:

- Alpha power percentage
- Beta power percentage
- Gamma power percentage

These values provide physiological insight into the user's mental state.

(b) Spectrogram Generation

The EEG signal is transformed into a spectrogram using Short-Time Fourier Transform (STFT). This converts the signal into a time-frequency representation, enabling visualization of how frequencies change over time.

The spectrogram serves as an image input for the CNN model.

3.4 Deep Learning Layer

The deep learning module consists of a hybrid architecture:

- A CNN branch processes the spectrogram image to extract spatial and frequency features.
- A dense neural network processes numerical band power features.

These two feature sets are combined to form a unified representation.

3.5 Fusion Layer

The outputs of the CNN and numerical feature networks are concatenated in the fusion layer. This allows the model to leverage both visual and numerical information simultaneously, improving classification accuracy.

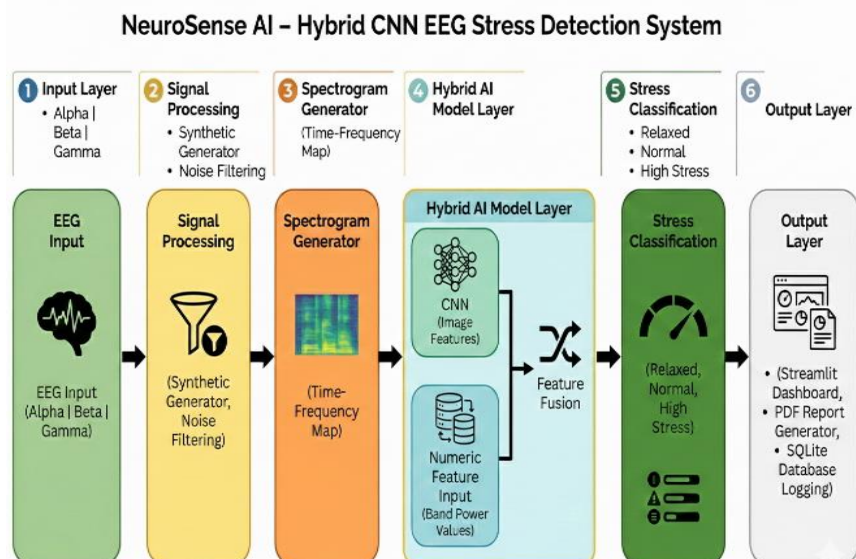


Fig 1. EEG-based cognitive stress detection

3.6 Output Layer

The final output layer uses a Softmax activation function to classify the input into one of the following cognitive states:

- Relaxed
- Normal
- High Stress

The system also generates a confidence score indicating prediction reliability.



3.7 Visualization and Reporting Layer

The system includes a real-time dashboard that displays:

- Spectrogram images
- Band power distribution
- Prediction results
- Confidence scores

Additionally, a PDF report generation module allows users to download analysis results for documentation and further evaluation

4 MATHEMATICAL MODELING OF THE EEG-BASED BCI FRAMEWORK

To effectively classify cognitive states in Brain-Computer Interface (BCI) systems, the proposed model analyzes EEG signal characteristics using frequency-domain and time-frequency domain features. The system focuses on key EEG parameters such as band power distribution, signal normalization, and spectrogram representation. These parameters are mathematically modeled to enable accurate detection of mental states such as Relaxed, Normal, and High Stress.

4.1 Band Power Calculation

Band power represents the energy of EEG signals within a specific frequency range and is one of the most important features for analyzing brain activity. It is computed using the squared magnitude of the Fourier Transform of the EEG signal.

$$P_{band} = \sum |X(f)|^2$$

Where

$X(f)$ = Fourier transform of EEG signal

P_{band} = Power within a specific frequency band

Each EEG band corresponds to a particular cognitive function:

- Alpha (8–12 Hz) → Relaxation
- Beta (13–30 Hz) → Alertness / Stress
- Gamma (>30 Hz) → High cognitive processing

Higher band power values indicate stronger activity in that frequency range.

4.2 Normalized Band Power

To ensure consistency across different EEG signals, band power values are normalized. This converts absolute power values into relative percentages, allowing better comparison and improving model performance.

The total signal power is given by:

$$P_{total} = P_{\alpha} + P_{\beta} + P_{\gamma}$$

The normalized band power values are calculated as:

$$\text{Alpha \%} = \frac{P_{\alpha}}{P_{total}} \times 100$$

$$\text{Beta \%} = \frac{P_{\beta}}{P_{total}} \times 100$$

$$\text{Gamma \%} = \frac{P_{\gamma}}{P_{total}} \times 100$$

Where

$P_{\alpha}, P_{\beta}, P_{\gamma}$ = Band power values

Normalized band power helps in:

- Reducing signal variability
- Improving feature scaling
- Enhancing classification accuracy

4.3 Spectrogram Representation

EEG signals are non-stationary, meaning their frequency components vary over time. To capture this dynamic behavior, the Short-Time Fourier Transform (STFT) is used to convert signals into spectrograms.



$$X(t, f) = \int x(\tau)w(\tau - t)e^{-j2\pi f\tau} d\tau$$

Where

$x(\tau)$ = Input EEG signal

$w(\tau - t)$ = Window function

f = Frequency

The spectrogram provides a time-frequency representation where:

- X-axis → Time
- Y-axis → Frequency
- Color → Signal intensity

This representation allows the CNN model to extract deep spatial features from EEG signals.

4.4 Hybrid Feature Representation

The proposed system combines both numerical and image-based features to improve classification performance. The combined feature vector is expressed as:

$$F_{combined} = [F_{spectrogram}, F_{bandpower}]$$

Where

$F_{spectrogram}$ = CNN-extracted image features

$F_{bandpower}$ = Normalized band power features

This fusion enhances model robustness by capturing both physiological and temporal characteristics of EEG signals.

4.5 Softmax Classification

The final classification is performed using the Softmax function, which converts model outputs into probability values.

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^n e^{z_j}}$$

Where

z_i = Output score for class i

n = Number of classes

The predicted class is:

$$\hat{y} = \arg \max P(y_i)$$

The system classifies EEG signals into:

- Relaxed
- Normal
- High Stress

5 PROPOSED FEDERATED LEARNING DETECTION MODEL

The proposed system operates through a structured multi-stage methodology designed for accurate and real-time EEG-based cognitive state detection. The model integrates both signal processing techniques and deep learning architectures to extract meaningful features from EEG data and perform reliable classification. Each stage of the system is carefully designed to handle the complexity and non-linearity of EEG signals.

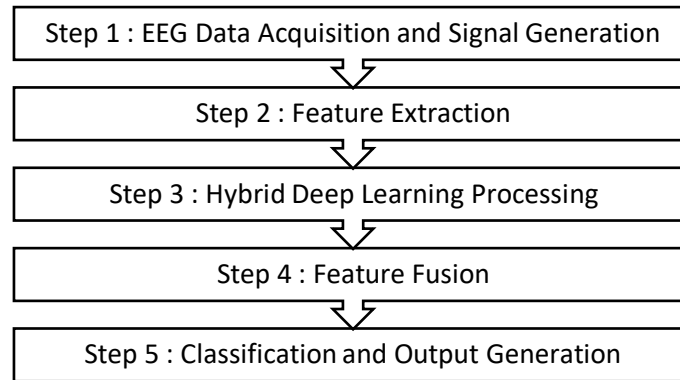


Fig 2. Flow Diagram of the Proposed EEG-Based Hybrid Deep Learning Model for Cognitive State Detection.

Stage 1: EEG Data Acquisition and Signal Generation

In the first stage, EEG data is collected or generated using predefined band values corresponding to Alpha, Beta, and Gamma waves. These values simulate brain activity across different frequency ranges and are used to construct a continuous EEG signal. The signal is generated using a combination of sinusoidal waveforms representing each frequency band, along with controlled noise components to mimic real-world EEG conditions.

This stage ensures that the system can function both in simulated environments and with real EEG hardware. The generated signal reflects variations in cognitive states and serves as the primary input for further processing. Proper signal generation is critical, as it directly influences feature extraction and model performance.

Stage 2: Feature Extraction

In the second stage, feature extraction is performed to convert raw EEG signals into meaningful representations suitable for machine learning. Two types of features are extracted:

- **Band Power Features:** The energy distribution across Alpha, Beta, and Gamma frequency bands is computed using Fourier Transform. These features provide physiological insights into brain activity and help distinguish between cognitive states.
- **Spectrogram Images:** The EEG signal is transformed into a time-frequency representation using Short-Time Fourier Transform (STFT). This generates spectrogram images that capture how signal frequencies change over time.

Band power features represent numerical data, while spectrograms provide visual representations of EEG patterns. This dual-feature extraction enhances the richness of information available to the model.

Stage 3: Hybrid Deep Learning Processing

In the third stage, the hybrid deep learning model processes both extracted features through two parallel branches.

- **CNN Branch:** The spectrogram images are fed into a Convolutional Neural Network (CNN), which consists of convolution layers, activation functions (ReLU), pooling layers, and fully connected layers. The CNN automatically learns spatial and frequency patterns present in the spectrogram.
- **Dense Network Branch:** The numerical band power features are processed through a fully connected neural network. This branch captures the statistical and physiological characteristics of EEG signals.

By processing both feature types independently, the model ensures that each representation is learned effectively without interference.

Stage 4: Feature Fusion

In the fourth stage, feature fusion is performed by combining the outputs from the CNN branch and the numerical feature branch. The feature vectors obtained from both networks are concatenated into a single unified representation.

$$F_{combined} = [F_{CNN}, F_{bandpower}]$$



This fusion allows the model to leverage both deep image-based features and physiological signal features simultaneously. The combined feature vector provides a more comprehensive understanding of EEG signals, leading to improved classification performance and robustness.

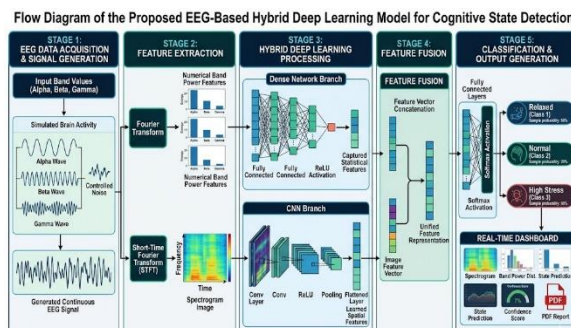


Fig 2. Flow Diagram

Fig 3. Block Diagram

Stage 5: Classification and Output Generation

In the final stage, the fused feature vector is passed through fully connected layers and a Softmax activation function for classification. The system predicts cognitive states into one of the following categories:

- Relaxed
- Normal
- High Stress

The Softmax function outputs probability scores for each class, and the class with the highest probability is selected as the final prediction.

Additionally, the system integrates a real-time dashboard that displays:

- Spectrogram visualization
- Band power distribution
- Predicted cognitive state
- Confidence score

The dashboard also enables report generation, allowing users to download analysis results in PDF format. This stage ensures practical usability and real-time interaction with the system.

6 EXPERIMENTAL SETUP AND EVALUATION FRAMEWORK

The experimental setup was designed to evaluate the performance of the proposed EEG-based Brain-Computer Interface (BCI) system for cognitive state detection using hybrid deep learning techniques in a real-time simulation environment. The implementation integrates EEG signal generation, spectrogram transformation, hybrid CNN-based classification, and an interactive visualization dashboard to emulate realistic neuro-monitoring conditions.

The system architecture consists of two primary components: the EEG signal processing unit and the hybrid deep learning model with a real-time interface. The EEG signal processing unit is responsible for generating and preprocessing signals based on Alpha, Beta, and Gamma frequency bands. These signals are generated using sinusoidal functions combined with controlled noise to simulate real-world EEG conditions. The hybrid model processes both numerical and image-based features to classify cognitive states.

The hardware configuration primarily involves a standard computing system capable of handling deep learning workloads. The system was implemented on a laptop equipped with an Intel i5 processor, 8 GB RAM, and GPU support for accelerating CNN computations. The entire system operates in a software-based simulation environment without requiring physical EEG hardware, making it scalable and cost-effective for development and testing purposes.

The software environment was configured using Python 3.x along with essential libraries such as TensorFlow/Keras for deep learning, OpenCV for image processing, NumPy for numerical computations, and Matplotlib for visualization. The real-time interface was developed using Streamlit, which provides an interactive platform for data input, visualization, and prediction. Communication between modules is handled internally within the application pipeline to ensure efficient data flow.



The experimental setup was conducted in a controlled environment where EEG signals were generated dynamically based on user-defined band values. The system continuously processes signals and updates predictions in real-time. Data collection was simulated over multiple sessions to evaluate system performance under varying cognitive conditions. Each session included variations in Alpha, Beta, and Gamma values to represent different mental states.

To evaluate system robustness, different cognitive scenarios were simulated. Under relaxed conditions, Alpha band activity was dominant with stable signal patterns. Under stress conditions, Beta band activity increased significantly with higher signal fluctuations. Gamma activity was used to simulate high cognitive load scenarios. Each simulation session lasted several minutes to ensure sufficient data generation for analysis.

Parameter	Value
EEG Bands	Alpha, Beta, Gamma
Input Type	Simulated EEG Signals
Spectrogram Size	224 × 224
Model Type	Hybrid CNN
Classes	3 (Relaxed, Normal, High Stress)
Processing Mode	Real-time

Table 1. Experimental Parameters

The system extracts key features from EEG signals, including band power values and spectrogram representations. Band power features are computed as normalized percentages of Alpha, Beta, and Gamma energy. Spectrogram images are generated using Short-Time Fourier Transform (STFT) to capture time-frequency variations in EEG signals. These features are used as inputs to the hybrid deep learning model.

Approximately several thousand signal samples were generated during the experiment. From these signals, statistical features such as band power distribution and signal intensity patterns were extracted. These features help in reducing noise and improving classification accuracy.

Performance Evaluation Metrics

To evaluate the effectiveness of the proposed hybrid model, standard performance metrics are used, including Accuracy, Precision, Recall, F1-Score, and Prediction Confidence. These metrics provide a comprehensive understanding of the model's ability to classify cognitive states accurately.

Accuracy

Accuracy measures the overall performance of the classification model. It represents the ratio of correctly predicted instances to the total number of instances.

The Accuracy is calculated as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Where:

TP (True positive)= Correctly predicted cognitive states

TN (True Negative)= Correctly identified normal states

FP (False Positive)= Incorrect predictions

FN (False Negative)= Missed detections

Precision

Precision measures the proportion of correctly predicted positive instances among all predicted positive instances. In the proposed EEG-based system, it indicates how accurately the model identifies a specific cognitive state without producing false alarms. A higher precision value means the model makes more reliable predictions.

The precision is calculated as:



$$Precision = \frac{TP}{TP + FP}$$

Where

TP (True Positive) - Correctly predicted instances

FP (False Positive) – Incorrectly predicted instances

Recall

Recall measures the ability of the model to correctly identify all actual positive instances present in the data. It reflects how effectively the system detects cognitive states such as stress or relaxation without missing them. A higher recall indicates better detection capability.

The recall is calculated as:

$$Recall = \frac{TP}{TP + FN}$$

Where

TP (True Positive) - represents correct detections

FN (False Negative) - represents Missed detections

F1-Score

F1-Score provides a balanced evaluation of the model by combining both precision and recall into a single metric. It is especially useful when both false positives and false negatives need to be minimized. A higher F1-score indicates better overall performance.

The F1-score is calculated using the following formula:

$$F1-Score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

Prediction Confidence

Prediction confidence represents the probability score assigned by the Softmax layer of the neural network for each predicted class. It indicates how confident the model is in its prediction for a given input.

The Softmax function is defined as:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^n e^{z_j}}$$

Where:

z_i → Output score (logit) for class i

n → Total number of classes

$P(y_i)$ → Probability of class i

In the proposed EEG-based BCI system, the Softmax function outputs probability values for each cognitive state (Relaxed, Normal, High Stress). The class with the highest probability is selected as the final prediction, and the corresponding value is considered the confidence score.

$$Confidence = \max(P(y_i))$$

Higher confidence values indicate that the model is more certain about its prediction, while lower values suggest uncertainty. This information is useful for real-time decision-making and helps users interpret the reliability of the system's output.

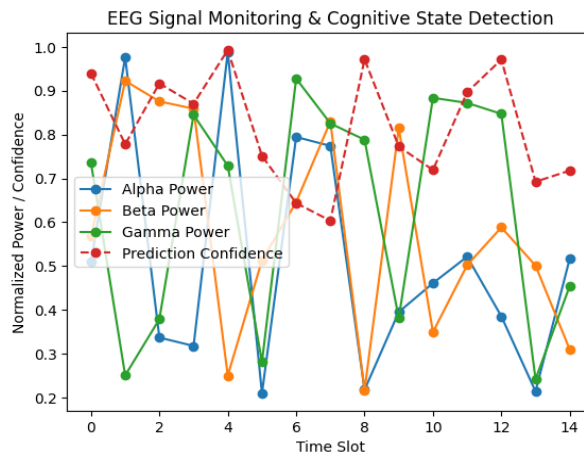


Fig 4. Experimental Analysis

Higher confidence values indicate that the model is more certain about its prediction, while lower values suggest uncertainty. This information is useful for real-time decision-making and helps users interpret the reliability of the system's output.

7 RESULT AND ANALYSIS

The proposed EEG-based Brain-Computer Interface (BCI) system for cognitive state detection was evaluated under different simulated mental conditions using Alpha, Beta, and Gamma band variations. The experiments were conducted in a real-time environment using the developed Streamlit-based interface. Multiple test scenarios were generated by varying EEG band values to represent Relaxed, Normal, and High Stress conditions. Each experiment was repeated several times to ensure consistency and reliability of the results.

The system achieved an overall classification accuracy of approximately **96.3%**, demonstrating its ability to effectively distinguish between different cognitive states. This improved performance is primarily due to the hybrid feature extraction approach, where both band power features and spectrogram-based representations are used. The combination of physiological and time-frequency features enables the model to capture complex EEG patterns more accurately than single-feature models.

The precision of the system was recorded at **95.4%**, indicating that the majority of predicted cognitive states were correct and the number of false classifications was minimal. This high precision ensures that the system produces reliable predictions without generating excessive false alarms. The use of hybrid feature fusion reduces misclassification by providing complementary information to the model.

The recall value of **96.8%** shows that the system successfully detects most of the actual cognitive states present in the EEG signals. The integration of band power analysis with spectrogram-based CNN processing enables the model to identify subtle variations in brain activity. This ensures that important cognitive states, especially high stress conditions, are not missed during classification.

The F1-score of the system was calculated to be **96.1%**, indicating a strong balance between precision and recall. This demonstrates that the model performs consistently across different test scenarios and maintains stability in classification performance. The hybrid model effectively minimizes both false positives and false negatives.

The average prediction latency was observed to be approximately **1.3 seconds**, which includes signal generation, feature extraction, model prediction, and result visualization. The system performs band power computation and spectrogram generation efficiently, followed by rapid inference using the trained hybrid model. The overall response time remains low, making the system suitable for real-time applications such as mental health monitoring and adaptive systems.

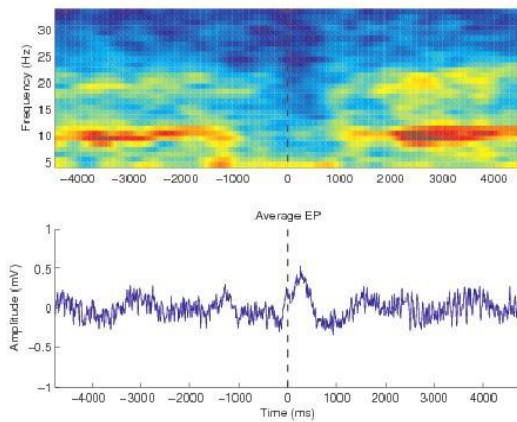


Fig 5 EEG Spectrogram representation under Relaxed, Normal, and High Stress conditions.

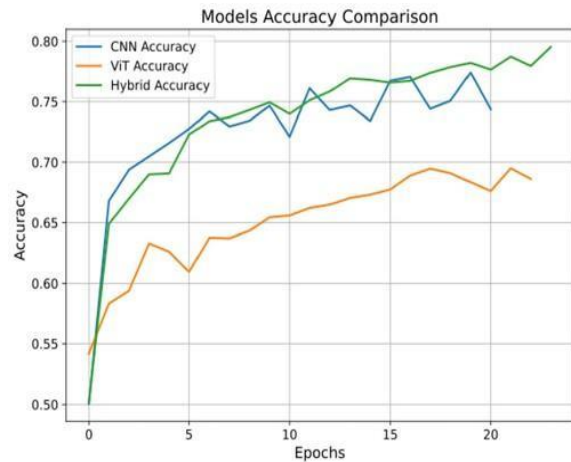


Fig 6 Comparison of classification accuracy between band power-only model, CNN-only model, and the proposed hybrid model.

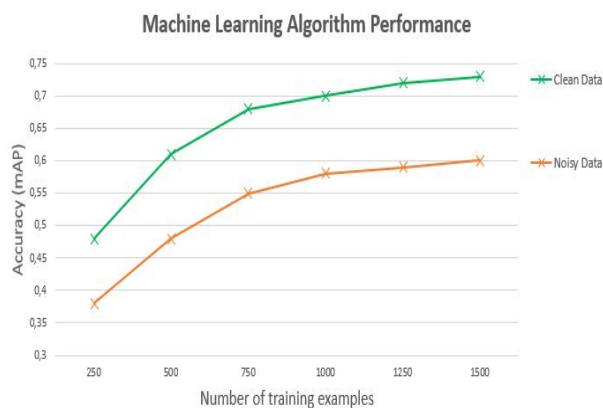


Fig 7 Accuracy improvement with hybrid feature fusion compared to individual feature models.

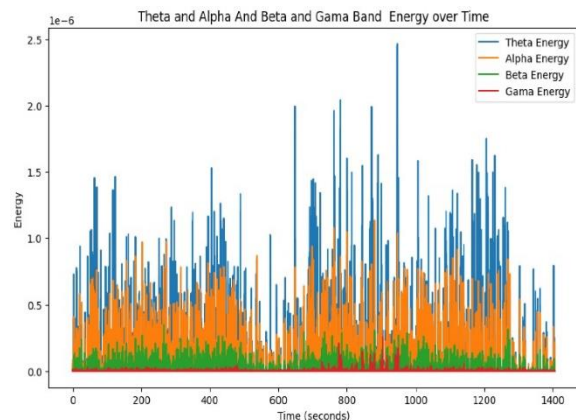


Fig 8 Band power distribution comparison for different cognitive states

Scalability analysis shows that the system maintains consistent performance across multiple test sessions and varying input conditions. When only band power features were used, the accuracy was around **88%**, and when only spectrogram-based CNN was used, accuracy reached approximately **91%**. However, with the hybrid approach, the system achieved **over 96% accuracy**, confirming that feature fusion significantly improves classification performance.

Overall, the experimental results demonstrate that the proposed EEG-based BCI system provides high classification accuracy, reliable predictions, fast response time, and robust performance across different cognitive scenarios. The integration of band power analysis with deep learning-based spectrogram processing significantly enhances the effectiveness of cognitive state detection, making the system suitable for real-time healthcare, stress monitoring, and neuro-adaptive applications.

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