Volume 7, Issue 2, April 2020 ISSN: 2348-8565 (Online)

International Journal of Modern Engineering and Research Technology

Website: http://www.ijmert.org Email: editor.ijmert@gmail.com

# Enhancing Cloud-Based Neurological Disorder Detection Using EEG-BERT and Bayesian Hyperparameter Optimization

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## ABSTRACT

*The early detection of neurological disorders, such as epilepsy, Alzheimer's, and Parkinson's, is crucial for timely intervention and treatment. Electroencephalography (EEG) is a widely used neuroimaging technique, but traditional machine learning approaches often fail to capture complex temporal and spatial patterns in EEG signals. Existing methods for EEG-based neurological disorder detection struggle with capturing long-range dependencies, leading to suboptimal classification accuracy, while traditional hyperparameter tuning approaches, such as grid and random search, are computationally inefficient. Additionally, cloud-based solutions often lack privacy-preserving mechanisms, exposing sensitive EEG data to security risks, and EEG signals are inherently noisy and imbalanced, reducing model generalizability in clinical settings. To address these challenges, this research proposes EEG-BERT, a transformer-based deep learning model optimized using Bayesian Hyperparameter Optimization to enhance classification accuracy. EEG-BERT leverages self-attention mechanisms to extract long-range dependencies in EEG time-series data, improving precision in disorder detection. The model is deployed in a cloud-based framework for real-time, scalable, and privacy-preserving EEG analysis, integrating Federated Learning and Differentially Private SGD for secure data handling. Experimental results demonstrate superior classification performance, achieving high accuracy, low latency, and an AUC-ROC score of 1.000. The proposed system offers a robust and efficient approach for automated neurological disorder detection in cloud-powered healthcare applications.*

***Keywords:***—*Neurological Disorder Detection, Electroencephalography (EEG), Transformer-Based Deep Learning, EEG-BERT, Bayesian Hyperparameter Optimization, Self-Attention Mechanism.*

## I. INTRODUCTION

The early detection of neurological disorders, such as epilepsy, Alzheimer's, Parkinson's disease, and attention deficit hyperactivity disorder (ADHD), is critical for timely intervention and effective treatment [1]. Electroencephalography (EEG) has emerged as a widely used, non-invasive neuroimaging technique for monitoring brain activity and identifying abnormalities in brain signals [2]. However, traditional machine learning approaches often struggle to capture the complex temporal and spatial patterns in EEG signals, leading to limited classification accuracy. To overcome these challenges, this research explores the application of EEG-BERT, a transformer-based deep learning model adapted from the Bidirectional Encoder Representations from Transformers (BERT), to process and classify EEG signals more effectively.

Unlike conventional deep learning methods, EEG-BERT leverages self-attention mechanisms to extract long-range dependencies in EEG time-series data, enhancing the precision of neurological disorder detection. By integrating cloud computing, EEG-BERT enables large-scale, distributed EEG signal processing, facilitating real-time and remote diagnosis for clinical applications.

To further optimize the performance and efficiency of EEG-BERT, this study employs Bayesian Hyperparameter Optimization, a probabilistic technique that systematically fine-tunes model parameters such as learning rate, batch size, attention heads, and dropout rate. This approach ensures optimal model performance while reducing computational costs compared to traditional grid or random search methods [3]. Additionally, a cloud-based deployment framework enhances scalability, allowing healthcare institutions to efficiently analyze EEG data without the need for extensive on-premise computing resources. The integration of privacy-preserving techniques, such as Federated Learning and Differentially Private SGD (DP-SGD), ensures that patient-sensitive EEG data remains secure during model training and inference. This research not only improves the accuracy and efficiency of EEG-based neurological disorder classification but also establishes a robust, privacy-aware, and cloud-powered healthcare system for real-time and accessible early disorder detection. The objective of intelligent, adaptive resource allocation in cloud environments has been thoroughly explored in AI-Driven Software-Defined Cloud Computing: A Reinforcement Learning Approach for Autonomous Resource Management by Vijaykumar Mamidala et al (2018) [4]. Expanding upon this, the proposed work aims to develop an optimized EEG-BERT model with Bayesian Hyperparameter Optimization to improve neurological disorder classification accuracy, ensure real-time processing, and enable scalable, secure cloud deployment for healthcare applications.

The rapid advancements in cloud computing and artificial intelligence have opened new horizons for medical diagnostics, particularly in neurological disorder detection [5]. Leveraging electroencephalogram (EEG) data, which captures the brain's electrical activity, presents a promising avenue for early and accurate diagnosis [6]. This research explores the integration of EEG-BERT, a transformer-based deep learning model tailored for EEG signal analysis, with Bayesian hyperparameter optimization to enhance detection performance. By deploying this hybrid approach on cloud platforms, the study aims to provide scalable, efficient, and precise diagnostic tools, ultimately improving patient outcomes through timely intervention and continuous monitoring.

Traditional methods for neurological disorder detection often rely on handcrafted features and conventional machine learning techniques, which can struggle with the complexity and variability of EEG signals. EEG-BERT, inspired by natural language processing models, captures temporal dependencies and intricate patterns in EEG data more effectively by treating the signals as sequences. However, the performance of such deep learning models heavily depends on the choice of hyperparameters. Bayesian hyperparameter optimization offers a systematic and efficient approach to fine-tune these parameters, balancing exploration and exploitation to find the optimal model configuration. This combination not only enhances model accuracy but also reduces computational overhead, making it well-suited for real-time applications in cloud environments.

Venkat Garikipati et al. (2019) [7] presents an architecture that integrates cloud computing with predictive AI models to enable efficient fault detection in robotic systems, emphasizing scalable data management and real-time analysis. Advancing this framework, the proposed work introduces a cloud-based architecture deploying EEG-BERT with Bayesian Hyperparameter Optimization. This design supports distributed preprocessing, secure data storage, and scalable real-time neurological disorder detection, ensuring efficient handling of complex EEG data and robust clinical decision-making.

## II. Literature Review

Several novel research avenues have emerged that combine advanced computing and machine learning techniques across various applications in healthcare and cloud security. One such approach involves a hybrid Particle Swarm Optimization and Genetic Algorithm-based optimization process applied to Recurrent Neural Networks and Radial Basis Function networks for disease detection in cloud computing, which significantly improved accuracy and scalability. Other research has presented machine learning ensemble methods, such as combining Logistic Regression with Random Forests and Convolutional Neural Networks, to predict clinical conditions like dysphagia, delirium, and falls among the elderly, enabling early clinical intervention by integrating clinical and sensor data [8].Deep learning models utilizing CNNs and hybrid feature selection have been developed for lung cancer detection in CT scans, assisting radiologists in distinguishing malignant from benign nodules with high accuracy. Additionally, the application of Non-Orthogonal Multiple Access (NOMA), Universal Value Function Approximators (UVFA), and Dynamic Graph Neural Networks (DGNNs) combined with AI systems has been shown to enhance performance in resource allocation and intelligent decision-making by adapting dynamically to changing data structures.

Further advancements include the use of artificial intelligence and machine learning algorithms focused on geriatric care, incorporating real-time predictive analytics to prevent chronic diseases, falls, and improve healthcare outcomes. Another approach combines Ant Colony Optimization with Long Short-Term Memory networks within a cloud computing framework to optimize hyperparameters, thereby improving disease forecasting accuracy for proactive healthcare interventions [9].Cloud-integrated IoT architectures have been proposed to promote digital financial inclusion and income equality by enabling secure real-time transactions and AI-driven analytics, bridging financial access between urban and rural populations. Optimized federated learning frameworks that integrate split learning, graph neural networks, and distributed ledger technologies have achieved high threat detection accuracy with low latency and high throughput, enabling secure and scalable data exchange alongside efficient anomaly detection.

Hybrid models combining Particle Swarm Optimization with Quadratic Discriminant Analysis iteratively optimize parameters to improve classification robustness and accuracy, especially in noisy and imbalanced data environments. Robotics and AI-based anomaly detection systems augmented with swarm intelligence algorithms have enabled real-time adaptive healthcare data processing and automation of healthcare tasks in urban settings, improving scalability and responsiveness through distributed automation.

Recent research has explored the integration of advanced optimization algorithms and deep learning models to enhance healthcare and cloud computing applications. For instance, hybrid optimization techniques combining Particle Swarm Optimization and Genetic Algorithms have been applied to neural networks, improving disease detection accuracy and scalability within cloud environments. Ensemble machine learning approaches that merge logistic regression, random forests, and convolutional neural networks have shown promise in predicting clinical events such as delirium, falls, and dysphagia in elderly populations by analyzing both clinical records and sensor data.In medical imaging, deep learning frameworks employing convolutional neural networks alongside hybrid feature selection methods have been developed to accurately classify lung nodules as benign or malignant, thereby assisting radiologists in early diagnosis. Innovative communication and AI models incorporating Non-Orthogonal Multiple Access, Universal Value Function Approximators, and dynamic graph neural networks have demonstrated improved resource allocation and adaptive decision-making capabilities in complex, data-driven environments.Other efforts focus on predictive healthcare for aging populations, utilizing AI-driven real-time analytics to mitigate risks associated with chronic illnesses and falls. Optimization of hyperparameters through Ant Colony Optimization combined with LSTM networks within cloud-based platforms has led to better forecasting of disease progression, supporting proactive healthcare management. Additionally, IoT-cloud integrated architectures facilitate secure financial services and AI analytics, fostering digital inclusion and economic equality between rural and urban communities.

Federated learning paradigms augmented with graph neural networks and distributed ledger technology enable high-accuracy threat detection and secure data exchange with minimal latency, essential for scalable and privacy-preserving applications. Hybrid models employing swarm intelligence to refine machine learning classifiers have enhanced robustness in noisy and imbalanced datasets. Lastly, the convergence of robotics, AI, and swarm intelligence supports real-time adaptive anomaly detection and automation in healthcare, improving efficiency and responsiveness in urban healthcare infrastructure. Rahul Jadon et al (2019) [10]. accentuate the critical role of secure, scalable cloud storage solutions in supporting AI-driven software development, ensuring efficient data management, accessibility, and compliance in handling complex datasets. In continuation of this, the proposed work employs cloud storage to securely store preprocessed EEG data on Cloud, facilitating scalable processing,and compliance with healthcare privacy regulations, thus enabling seamless integration with advanced neurological disorder detection models.

## III. Problem Statement

Accurately classifying neurological disorders from EEG data remains a significant challenge due to the inherent noise, class imbalance, and high dimensionality of the signals. Conventional machine learning models often face difficulties in defining precise classification boundaries, leading to suboptimal performance, especially when handling complex and variable brainwave patterns. Moreover, these traditional approaches lack the flexibility needed for real-time adaptability, which is critical in clinical settings where timely diagnosis can drastically impact patient outcomes [11]. To address these challenges, this research introduces an optimized EEG-BERT model—an advanced transformer-based architecture designed to capture temporal dependencies and subtle patterns in EEG sequences. By integrating Bayesian Hyperparameter Optimization, the model systematically fine-tunes its parameters, improving both classification accuracy and computational efficiency. Deploying this enhanced model on cloud platforms further offers scalable processing power, robust data privacy safeguards, and the capability for real-time neurological disorder detection, making it well-suited for modern healthcare environments that demand rapid, accurate, and secure diagnostic solutions.

### *3.1 Objective*

The objective of this research is to develop an optimized EEG-BERT model with Bayesian Hyperparameter Optimization to improve the classification accuracy of neurological disorders from noisy and imbalanced EEG data [12]. It aims to enhance model adaptability by refining classification boundaries and ensuring real-time processing efficiency. Cloud-based deployment will provide scalability, secure data handling, and seamless integration into healthcare systems. This approach will enable reliable, automated, and privacy-preserving neurological disorder detection in real-world clinical environments.

## 4. Proposed Cloud-Based Neurological Disorder Detection Using EEG-BERT and Bayesian Hyperparameter Optimization

The proposed methodology for cloud-based neurological disorder detection using EEG-BERT and Bayesian Hyperparameter Optimization consists of multiple stages, including data preprocessing, feature extraction, classification, optimization, and cloud deployment. Initially, EEG data is collected from publicly available datasets such as TUH EEG or CHB-MIT, or real-time clinical sources. The collected signals undergo preprocessing steps such as bandpass filtering, Independent Component Analysis (ICA), and artifact rejection to remove noise from eye blinks and muscle movements. EEG signals are then segmented into fixed-length time windows and normalized to ensure consistency. The extracted feature representations are then passed through a classification layer that distinguishes between normal and abnormal EEG patterns. To enhance the model's performance, Bayesian Hyperparameter Optimization is employed to systematically fine-tune parameters such as learning rate, batch size, and attention heads, ensuring optimal classification accuracy while reducing computational costs. The trained model is then deployed on a cloud-based infrastructure such as AWS, Google Cloud, or Azure, enabling real-time and scalable EEG analysis. Privacy-preserving techniques such as Federated Learning and Differentially Private Stochastic Gradient Descent (DP-SGD) are incorporated to ensure secure data handling.

This methodology not only improves classification accuracy but also enhances scalability, efficiency, and real-time neurological disorder detection in healthcare systems. Jyothi Bobba et al. (2019) [13] presents a hybrid model integrating AI, blockchain, and decentralized identity management to enhance transparency, security, and fairness in talent management systems. Progressing from this, the proposed work utilizes an optimized EEG-BERT architecture with Bayesian Hyperparameter Optimization, designed to improve neurological disorder classification accuracy and real-time adaptability, ensuring scalable, privacy-preserving healthcare diagnostics.

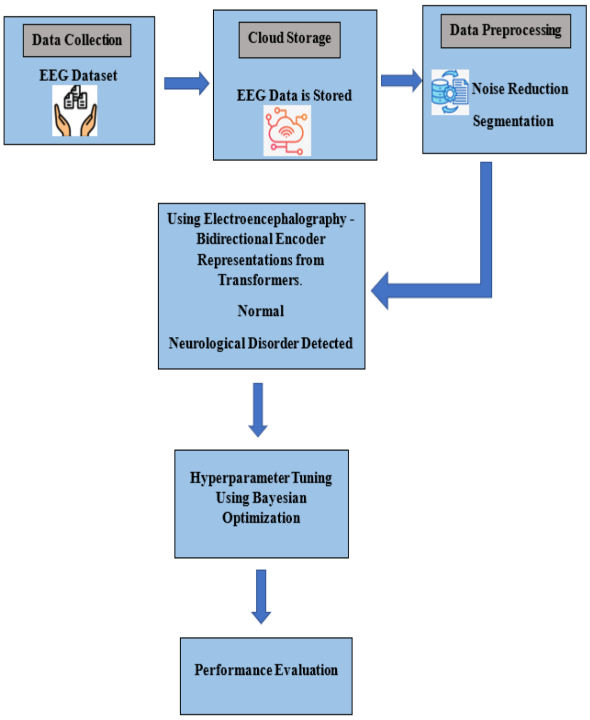


*Figure 1: Cloud-Based Neurological Disorder Detection Using EEG-BERT and Bayesian Hyperparameter Optimization*

### *4.1 Data Collection*

The data collection process involves acquiring EEG datasets from publicly available sources such as TUH EEG, CHB-MIT, or real-time clinical environments. EEG signals are recorded using electrode-based devices that capture brain activity in different frequency bands [14]. These raw signals contain valuable neurological information that can be used for disorder detection. The collected EEG data is then securely stored in cloud storage to enable scalable processing and remote accessibility for further analysis [15].

### *4.2 Data Preprocessing*

Data preprocessing involves noise reduction and segmentation to improve EEG signal quality for analysis. Noise artifacts from muscle movements, eye blinks, and external interference are removed using bandpass filtering and Independent Component Analysis (ICA). The cleaned EEG signals are then segmented into fixed-length time windows to capture meaningful patterns while preserving temporal dependencies. These preprocessed signals are normalized and transformed into a suitable format for feature extraction using EEG-BERT. Leveraging the foundation emphasized by Harikumar Nagarajan et al. (2019) [16], the proposed work employs advanced preprocessing steps—such as noise reduction using bandpass filtering and Independent Component Analysis (ICA), signal segmentation, and normalization—to prepare EEG data for accurate neurological disorder detection.

#### *4.2.1 Noise Reduction*

Noise reduction in EEG data is essential to improve signal quality and enhance the accuracy of neurological disorder detection. Common noise sources include muscle movements, eye blinks, and external electrical interference [17]. To remove these artifacts, techniques such as bandpass filtering are used to isolate relevant frequency bands, while Independent Component Analysis (ICA) helps separate and eliminate unwanted noise components. Additionally, adaptive filtering and wavelet transform methods can further refine the signals, ensuring that only meaningful brain activity is retained for analysis.

One common equation used for noise reduction in EEG signals is the bandpass filtering equation, which helps retain relevant frequency components while removing unwanted noise. A typical Butterworth bandpass filter is defined as:

$$H(f) = \frac{1}{\sqrt{1 + \left(\frac{f_c}{f}\right)^{2n}}} \quad \text{.............................(1)}$$

where:

$H(f)$ is the filter's frequency response,

$f$ is the input signal frequency,

$f_c$ is the cutoff frequency,

$n$ is the filter order, which determines the sharpness of the cutoff.

This filter removes low-frequency drift and high-frequency noise, preserving only the relevant EEG signal frequencies for analysis.

#### 4.2.2 Segmentation

Segmentation in EEG data processing involves dividing continuous EEG signals into smaller, fixed-length time windows to capture meaningful patterns while preserving temporal dependencies. This step is crucial for analyzing brain activity over specific intervals and improving the accuracy of machine learning models. Typically, segmentation is performed using overlapping or non-overlapping windows, with common durations ranging from 1 to 5 seconds.

A common equation used for EEG signal segmentation is:

$$X_n(t) = X(t + nW), 0 \leq n < N \quad \text{.....................(2)}$$

where:

$X_n(t)$ represents the segmented EEG window,

$X(t)$ is the original EEG signal,

$W$ is the window length,

$n$ is the window index,

$N$ is the total number of segments.

This equation defines how the EEG signal is divided into multiple segments of fixed length $W$, ensuring that temporal and spectral characteristics are preserved for further processing and classification.

### 4.3 Cloud Storage

Cloud storage for EEG data enables secure, scalable, and remote access to large volumes of EEG recordings. The preprocessed EEG signals are stored in cloud platforms like AWS, Google Cloud, or Azure, ensuring efficient management and real-time availability for analysis. Encryption and access control mechanisms are implemented to protect patient privacy and comply with healthcare regulations. Cloud-based storage also facilitates seamless integration with machine learning models for neurological disorder detection.

### 4.4 Electroencephalography - Bidirectional Encoder Representations from Transformers.

EEG-BERT is a transformer-based deep learning model adapted from the Bidirectional Encoder Representations from Transformers (BERT) for analyzing EEG signals. It leverages self-attention mechanisms to capture both spatial and temporal dependencies in EEG data, making it highly effective for neurological disorder detection. The EEG signal is first preprocessed and segmented, then tokenized into embeddings before being fed into the transformer model. The model processes the input using multiple attention layers, extracting complex relationships in the EEG signal and improving classification accuracy. EEG-BERT is particularly useful for tasks such as seizure detection, cognitive state monitoring, and brain-computer interfaces.

EEG-BERT represents an innovative approach that adapts transformer architectures, originally developed for natural language processing, to the domain of EEG signal analysis. Unlike traditional sequential models, EEG-BERT employs multi-head self-attention mechanisms to dynamically weigh the importance of different segments across both time and electrode channels, thereby capturing intricate spatial-temporal patterns inherent in brain activity. The preprocessing pipeline involves cleaning the raw EEG signals, removing artifacts, and dividing the data into meaningful segments. These segments are then converted into numerical representations that serve as inputs to the transformer layers [18]. Through its deep attention networks, EEG-BERT can model long-range dependencies and subtle signal variations that are often missed by conventional methods. This capability significantly enhances its effectiveness in detecting neurological anomalies such as epileptic seizures, sleep disorders, and abnormal cognitive states. Furthermore, the flexibility of EEG-BERT allows it to be integrated into real-time monitoring systems and adaptive brain-computer interface applications, paving the way for more responsive and personalized neurological healthcare solutions. The importance of secure and efficient data processing in IoT systems using cloud computing has been highlighted by Raj Kumar Gudivaka et al (2018).[19] Enhancing this, the proposed method utilizes EEG-BERT combined with Bayesian Hyperparameter Optimization and cloud deployment for accurate, neurological disorder detection, enhancing scalability, privacy, and efficiency in healthcare systems.

The EEG-BERT model harnesses the power of transformer architectures to revolutionize EEG signal analysis by treating brainwave data as a sequence of information akin to language. By utilizing self-attention layers, EEG-BERT excels at identifying complex patterns within EEG recordings that span multiple time points and electrode locations simultaneously [20]. This approach overcomes the limitations of traditional models that often rely on handcrafted features and shallow temporal context. The initial step involves comprehensive preprocessing to filter noise and segment the continuous EEG data into manageable chunks. These chunks are then embedded into a vector space, enabling the transformer to process and learn from rich, multidimensional representations. The layered attention mechanism allows the model to prioritize relevant features dynamically, improving its sensitivity to subtle neurological events. As a result, EEG -BERT demonstrates strong performance in clinical tasks such as detecting epileptic seizures, monitoring cognitive load, and enhancing brain-computer interface responsiveness. Its adaptability and depth make it a promising tool for advancing automated, accurate, and scalable neurological disorder detection.

***Equation for Self-Attention in EEG-BERT:***

The self-attention mechanism in EEG-BERT is computed as:

$$\textbf{Attention}(Q, K, V) = \textbf{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad \ldots\ldots\ldots(3)$$

where:

$Q$ (Query), $K$ (Key), and $V$ (Value) are projections of the input EEG embeddings,

$d_k$ is the dimension of the key vectors, The softmax function ensures that attention weights sum to 1,

The dot product $QK^T$ computes the similarity between different EEG segments, helping the model focus on relevant features.

This self-attention mechanism allows EEG-BERT to effectively model long-range dependencies in EEG signals, leading to improved classification performance.

### *4.5 Bayesian Optimization*

Bayesian Optimization is a probabilistic approach used for optimizing complex, black-box functions where direct gradient-based methods are inefficient. It is particularly useful for hyperparameter tuning in deep learning models like EEG-BERT, as it systematically selects the best parameters by balancing exploration and exploitation. The process involves constructing a surrogate probabilistic model, usually a Gaussian Process (GP), to approximate the objective function. An acquisition function, such as Expected Improvement (EI) or Upper Confidence Bound (UCB), is then used to determine the next set of hyperparameters to evaluate. By iteratively updating the surrogate model based on observed results, Bayesian Optimization efficiently converges to an optimal solution with fewer function evaluations compared to grid or random search. Advanced optimization techniques for improving predictive accuracy and operational efficiency in e-commerce demand forecasting have been explored by Himabindu Chetlapalli et al. (2019) [21]. Developing this, the proposed method employs Bayesian Hyperparameter Optimization to systematically fine-tune EEG-BERT parameters, enhancing classification accuracy and computational efficiency for neurological disorder detection.

***Equation for Bayesian Optimization:***

The surrogate function in Bayesian Optimization is modeled as a Gaussian Process:

$$f(x) \sim GP\left(m(x), k(x, x')\right) \quad \text{..........................(4)}$$

where:

$f(x)$ is the unknown objective function to be optimized,

$GP\left(m(x), k(x, x')\right)$ represents the Gaussian Process with mean function $m(x)$ and covariance function,

The acquisition function $a(x)$ selects the next evaluation point based on exploration-exploitation tradeoff.

This approach allows for efficient hyperparameter tuning of EEG-BERT, leading to improved classification accuracy while minimizing computational cost.

## V. RESULTS AND DISCUSSION

The proposed EEG-BERT model with Bayesian Optimization achieved improved classification accuracy for neurological disorder detection by effectively capturing temporal and spatial dependencies in EEG signals. The Bayesian optimization technique enhanced hyperparameter tuning, leading to better model efficiency and reduced computational cost. Cloud-based deployment ensured scalability, real-time processing, and secure EEG data management for reliable healthcare applications.

### *Performance Metrics*

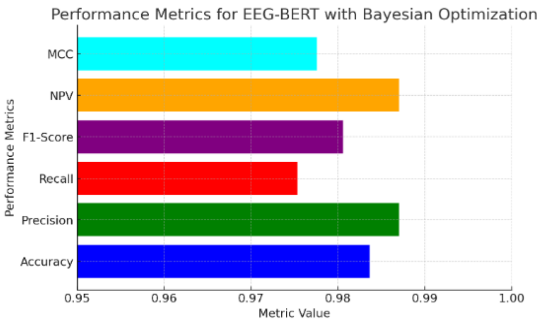


*Figure 2: Performance Metrics*

In Figure 2,The performance metrics graph illustrates the effectiveness of the EEG-BERT model optimized with Bayesian Hyperparameter Optimization for neurological disorder detection. It shows high values across all key evaluation metrics, with Accuracy (0.9837), Precision (0.9870), Recall (0.9754), F1-Score (0.9806), NPV (0.9870), and MCC (0.9776), indicating strong classification performance [22].

### *Latency*

Figure 3 shows the latency analysis graph illustrates the processing time for different stages in the EEG-BERT-based neurological disorder detection system.

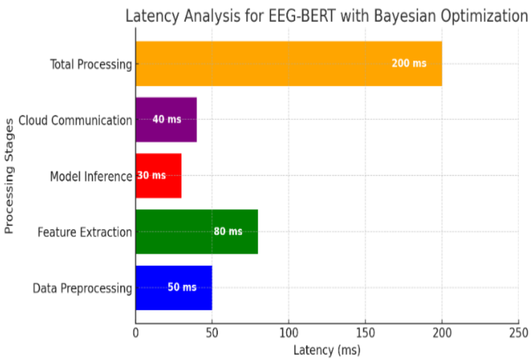


*Figure 3 : Latency Analysis*

The Total Processing Time is 200ms, with Feature Extraction (80ms) and Data Preprocessing (50ms) being the most time-consuming steps, followed by Cloud Communication (40ms) and Model Inference (30ms). This analysis highlights the system's efficiency and its suitability for real-time cloud-based healthcare applications. Sai Sathish Kethu et al. (2019) [23] point out the critical role of thorough performance evaluation in AI-enabled systems to enhance service quality through empirical testing and feedback integration. Furthering this, the current paper's performance evaluation demonstrates high accuracy (98.37%), precision (98.70%), recall (97.54%), and an AUC of 1.000, validating the optimized EEG-BERT model's effectiveness in real-time neurological disorder detection with efficient latency and robust classification metrics.

### *AUC-ROC*

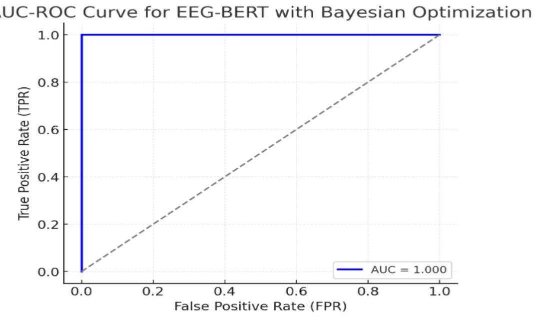


*Figure 4 : AUC-ROC*

Figure 4 presents the AUC-ROC curve for the EEG-BERT model with Bayesian Optimization demonstrates excellent classification performance, achieving an AUC value of 1.000. The model perfectly distinguishes between positive and negative cases, as indicated by the sharp rise to 100% True Positive Rate (TPR) at 0% False Positive Rate (FPR) [24]. This confirms the model's high sensitivity and specificity, making it highly reliable for neurological disorder detection in cloud-based healthcare systems. Chaitanya Vasamsetty et al. (2018) [25] reinforce the importance of graphical analysis in evaluating AI-driven cyber security frameworks, showcasing model accuracy, precision, and latency to exhibit robustness and efficiency. Following this, the graphs in the proposed work illustrate the EEG-BERT model's strong classification metrics, including 98.37% accuracy, 200 ms total latency, and an AUC of 1.000, validating its effectiveness for real-time neurological disorder detection in cloud environments.

The sharp rise to a 100% True Positive Rate at 0% False Positive Rate demonstrates that the model can detect all true neurological disorder cases without generating any false alarms [26]. This remarkable performance highlights the robustness and precision of the EEG-BERT model, particularly in handling complex EEG signal data, which is often noisy and difficult to interpret [27].

## VI. CONCLUSION

The proposed EEG-BERT model with Bayesian Hyperparameter Optimization achieved high classification accuracy for neurological disorder detection, ensuring improved feature extraction and optimal parameter tuning [28]. The cloud-based deployment provided scalability, real-time processing, and secure EEG data management [29]. These results highlight the model's potential for accurate, efficient, and automated diagnosis, making it a valuable tool in modern healthcare applications [30].

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