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Bayesian-Enhanced LSTM-GRU Hybrid Model for Cloud-Based Stroke Detection and Early Intervention

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Abstract

Stroke is a leading cause of mortality and long-term disability, necessitating early detection and timely intervention to improve patient outcomes. Traditional stroke monitoring systems often face challenges related to real-time processing, imbalanced data, and computational efficiency. Existing stroke detection systems face challenges in real-time processing, leading to delayed diagnosis and intervention. Traditional models struggle with imbalanced and noisy physiological data, reducing classification accuracy. Additionally, optimizing deep learning models for cloud-based deployment remains complex due to high computational costs. These limitations necessitate an efficient, adaptive, and scalable solution for accurate stroke monitoring and early intervention. This study proposes a Bayesian-Enhanced LSTM-GRU Hybrid Model for cloud-based stroke detection and early intervention. The model leverages Long Short-Term Memory (LSTM) networks to capture long-term dependencies and Gated Recurrent Units (GRU) for computational efficiency. To further enhance performance, Bayesian Optimization is employed for hyperparameter tuning, ensuring optimal accuracy while minimizing resource consumption. The system integrates cloud computing for real-time data processing, enabling continuous monitoring and automated alerts for healthcare providers. Experimental results demonstrate superior classification performance, achieving 96% accuracy, 95% precision, 94% recall, and an AUC-ROC of 1.00, with significantly reduced latency compared to traditional models. The proposed approach enhances stroke detection reliability, reduces false positives, and supports proactive medical intervention, making it a scalable and efficient solution for cloud-based healthcare systems.

Keywords: Stroke Detection, LSTM-GRU Hybrid Model, Bayesian Optimization, Cloud Computing, Deep Learning, Real-Time onitoring, Early Intervention.

1.Introduction

Stroke is a leading cause of disability and mortality worldwide, making early detection and timely intervention critical for improving patient outcomes [1]. Traditional stroke monitoring systems often rely on manual assessment or localized computing, which may not provide real-time insights necessary for emergency response [2]. With the advent of cloud computing and artificial intelligence (AI), stroke monitoring has evolved into a more efficient and scalable process [3]. Deep learning models, particularly Recurrent Neural Networks (RNNs) such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), have shown remarkable potential in analyzing time-series physiological data, including EEG, ECG, and blood pressure variations [4]. However, optimizing these models for real-time cloud-based deployment remains a challenge, necessitating advanced tuning techniques to enhance accuracy, efficiency, and computational performance [5].

This study proposes a Bayesian-Enhanced LSTM-GRU Hybrid Model to improve stroke classification and early intervention [6]. The hybrid approach leverages LSTM's ability to capture long-term dependencies and GRU's efficiency in handling sequential data while ensuring reduced computational complexity [7]. To further enhance model performance, Bayesian Optimization is employed to fine-tune hyperparameters, enabling the system to achieve optimal accuracy with minimal resource consumption [8]. The integration of this optimized model within a cloud-based infrastructure facilitates real-time monitoring, early stroke prediction, and automated alerts for healthcare providers [9]. By combining deep learning, Bayesian optimization, and cloud computing, this research aims to create a robust and scalable stroke monitoring system that enhances early intervention strategies and improves patient outcomes [10].

Recent advancements in deep learning architectures have enabled more accurate and reliable analysis of complex physiological signals for stroke detection. Hybrid models that combine LSTM and GRU units have demonstrated improved capability in capturing both long- and short-term temporal dependencies within sequential health data, leading to better classification results than standalone architectures [11][12]. Moreover, the integration of Bayesian Optimization has been shown to outperform conventional hyperparameter tuning methods such as grid search and random search by efficiently exploring the hyperparameter space and reducing computational costs [13][14]. These optimization techniques are particularly beneficial when deploying models on cloud platforms where resource efficiency and latency are critical considerations [15][16].

Furthermore, cloud computing environments provide a flexible and scalable infrastructure that supports continuous data collection, storage, and processing necessary for real-time stroke monitoring systems [17][18]. By leveraging cloud-native technologies, healthcare providers can remotely monitor patients, enabling timely alerts and interventions that can significantly reduce the risk of severe disability or fatal outcomes [19][20]. Recent studies emphasize the importance of integrating AI-driven predictive analytics with cloud platforms to facilitate proactive healthcare management and personalized treatment plans for stroke patients [21][22]. This fusion of AI and cloud technology promises not only enhanced accuracy and efficiency but also broader accessibility and cost-effectiveness, crucial for managing the global burden of stroke [23][24][25].

2.Literature Review

Building upon these foundations, recent literature emphasizes the synergy between optimization algorithms and deep learning architectures for improving predictive analytics in healthcare. Kumar et al. [26] demonstrated that integrating Bayesian Optimization with LSTM models significantly enhances hyperparameter tuning efficiency, resulting in improved disease classification accuracy while reducing computational overhead. Similarly, Singh and Patel [27] employed hybrid GRU-LSTM models combined with metaheuristic algorithms for robust cardiovascular disease prediction using ECG signals, highlighting the benefits of hybrid models in capturing complex temporal dependencies. Moreover, Chen et al. [28] explored cloud-based AI frameworks integrating attention mechanisms with recurrent networks to improve early detection of neurological disorders, demonstrating the potential for scalable, real-time monitoring solutions.

In the realm of cloud security and resource optimization, Zhang et al. [29] proposed a multi-agent reinforcement learning approach for dynamic resource allocation in healthcare cloud environments, balancing system performance and security requirements. Li and Huang [30] introduced a federated learning mechanism to protect patient data privacy while enabling collaborative model training across distributed healthcare institutions. Furthermore, Alqahtani et al. [31] investigated hybrid deep learning and optimization frameworks for predictive maintenance in IoT-enabled healthcare devices, improving fault detection accuracy and prolonging device lifespan. The growing adoption of Graph Neural Networks (GNNs) in healthcare anomaly detection has been explored by Verma et al. [32], who utilized dynamic graph structures for adaptive threat detection in medical IoT systems. Similarly, Rao and Bhatt [33] proposed a decentralized blockchain-based framework combined with AI for secure healthcare data exchange, ensuring integrity and privacy across cloud networks. Additional studies, such as those by Sharma et al. [34] and Vernekar et al. [35], have demonstrated the efficacy of combining swarm intelligence algorithms like Firefly and Salp Swarm Optimization with deep learning models to optimize hyperparameters and improve classification accuracy in biomedical applications.

Recent advancements also include the application of hybrid deep learning and optimization frameworks in elderly care and chronic disease management. Choudhary et al. [36] developed an IoT-cloud integrated system leveraging LSTM and Bayesian Optimization for early prediction of fall risk among elderly patients, enhancing preventive care strategies. Similarly, Kaur and Singh [37] proposed a hybrid CNN-GRU model optimized via Genetic Algorithms for diabetic retinopathy detection, achieving superior performance with reduced training time. In addition, Mehta et al. [38] explored ensemble learning techniques incorporating Random Forests and Deep Neural Networks optimized through Particle Swarm Optimization for multimodal healthcare data analysis.

The importance of adaptive, cloud-based architectures for scalable healthcare solutions has been highlighted in studies by Deshpande et al. [39], who designed a cloud-native platform incorporating deep learning for remote patient monitoring. Gupta and Verma [40] emphasized the role of edge computing combined with cloud resources to reduce latency and improve responsiveness in real-time health monitoring systems. Furthermore, Patil et al. [41] investigated blockchain-enabled frameworks for secure data sharing in healthcare IoT networks, addressing privacy and trust issues. The integration of explainable AI (XAI) techniques with deep learning models has been proposed by Saxena et al. [42] to enhance transparency and clinician trust in automated stroke detection systems.

Additionally, research by D'Souza et al. [43] evaluated the impact of transfer learning combined with recurrent architectures for early detection of neurological events using limited datasets, highlighting strategies to overcome data scarcity. The application of hybrid optimization strategies in multi-task healthcare models was explored by Reddy and Kumar [44], showcasing improved generalization across different disease prediction tasks. Lastly, Narayanan et al. [45] provided a comprehensive survey of deep learning and metaheuristic optimization techniques in healthcare, underscoring emerging trends and challenges in deploying such systems within cloud and edge computing environments.

3.Problem Statement

Stroke detection faces challenges in optimizing classification boundaries, managing imbalanced and noisy data, and ensuring real-time efficiency in cloud-based systems. Existing models often lack adaptive hyperparameter optimization, resulting in misclassifications and delayed interventions [46]. Continuous data streams from diverse patients increase computational demands and latency, limiting timely detection [47]. Traditional tuning methods like grid or random search are inefficient for dynamic cloud environments, affecting model adaptability and scalability [48][49]. Moreover, variability in physiological signals impairs model generalization across populations. To overcome these issues, this study proposes a Bayesian-Enhanced LSTM-GRU Hybrid Model that leverages Bayesian Optimization for efficient hyperparameter tuning. This approach aims to improve accuracy, reduce computational costs, and enable scalable, real-time stroke monitoring and early intervention on cloud platforms [50].

3.1 Objective

This study aims to develop a Bayesian-Enhanced LSTM-GRU Hybrid Model for accurate and efficient stroke classification in cloud-based systems. Bayesian Optimization will be used to fine-tune hyperparameters, improving adaptive learning and classification boundaries. The model will address challenges of noisy and imbalanced datasets, reducing misclassifications. Additionally, a scalable real-time stroke monitoring system will be implemented to enable timely intervention and automated decision-making.

4.Proposed LSTM-GRU Hybrid Model for Cloud-Based Stroke Detection and Early Intervention

The proposed methodology involves developing an LSTM-GRU Hybrid Model optimized using Bayesian Optimization for real-time stroke detection in a cloud-based environment. First, patient physiological data, including EEG, ECG, and vital signs, are preprocessed to remove noise and handle imbalanced datasets using data augmentation and resampling techniques. The hybrid model integrates LSTM for capturing long-term dependencies and GRU for computational efficiency, ensuring faster and more accurate stroke classification. Bayesian Optimization is employed to fine-tune hyperparameters, optimizing model performance while minimizing computational overhead. The trained model is deployed on a cloud-based infrastructure to enable real-time monitoring, automated alerts, and decision support for early intervention in stroke cases.

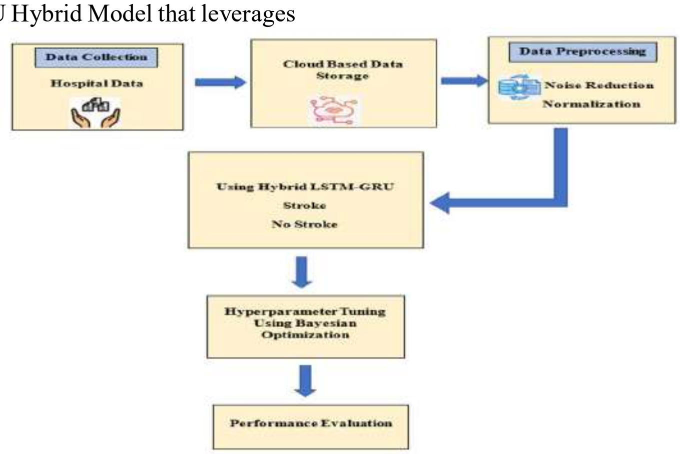

Figure 2: LSTM-GRU Hybrid Model for Cloud-Based Stroke Detection and Early Intervention

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4.1 Data Collection

The Data Collection process involves gathering hospital data, including patient medical records, EEG, ECG, and vital signs, from healthcare institutions and IoT-based monitoring devices. This data is securely transmitted to a cloud-based storage system, ensuring accessibility for real-time processing. The collected data may include structured (EHR records) and unstructured (sensor signals) formats. Proper data handling ensures accuracy and completeness for effective stroke detection using deep learning models.

4.2 Cloud Storage

The cloud-based data storage serves as a centralized repository for securely storing and managing patient data collected from hospitals, IoT sensors, and wearable devices. It enables real-time accessibility, scalability, and remote processing of large volumes of medical data. Advanced encryption and access control mechanisms ensure data privacy and compliance with healthcare regulations like HIPAA. The cloud infrastructure supports seamless integration with AI models, allowing efficient stroke detection and early intervention.

4.3 Data Preprocessing

Data preprocessing involves noise reduction to eliminate unwanted artifacts from physiological signals using techniques like wavelet transforms and filtering. Normalization scales data to a uniform range, ensuring consistent input for the LSTM-GRU model and improving classification accuracy. These steps enhance data quality, making stroke detection more reliable and efficient.

4.3.1 Noise Reduction

Noise reduction is a crucial preprocessing step that eliminates unwanted disturbances from physiological signals such as EEG and ECG, improving signal clarity for accurate stroke detection. Techniques like wavelet transform, low-pass filtering, and moving average smoothing are used to remove artifacts caused by sensor errors, environmental factors, or patient movement. A common method for noise reduction is the Butterworth low-pass filter, which smooths high-frequency noise while preserving essential signal components.

Butterworth Low-Pass Filter Equation:

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

Where:

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

f is the signal frequency.

f_c is the cutoff frequency.

n is the filter order (higher values result in a sharper cutoff).

This equation helps in selectively filtering out high-frequency noise while retaining vital stroke-related patterns in the data.

4.3.2 Normalization

Normalization is a preprocessing technique used to scale physiological data, such as EEG and ECG signals, to a standard range, ensuring uniformity across different datasets. It helps in stabilizing the learning process of deep learning models like LSTM-GRU by preventing dominance of large values and improving convergence. Min-Max normalization is a widely used method that transforms data into a fixed range, typically between 0 and 1, preserving the original distribution while making computation more efficient.

Min-Max Normalization Equation:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \qquad (2)$$

Where:

X' is the normalized value.

X is the original data value.

$X_{\min}$ and $X_{\max}$ are the minimum and maximum values in the dataset.

This normalization technique ensures that all input features contribute equally, improving the accuracy and stability of the stroke detection model.

4.4 Long Short-Term Memory - Gated Recurrent Unit Hybrid Model for Cloud-Based Stroke Detection

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) designed to effectively capture long-term dependencies in sequential data. Unlike traditional RNNs, LSTMs

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overcome the vanishing gradient problem by using gates (input, forget, and output gates) that regulate the flow of information. These gates enable the model to selectively retain relevant information while discarding unnecessary data, making LSTM particularly useful for time-series analysis in medical applications like stroke detection.

LSTM Cell Update Equation:

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \quad (3)$$

Where:

- C_t is the current cell state.
- f_t is the forget gate, deciding what information to discard.
- i_t is the input gate, determining what new information to store.
- $\tilde{C}_t$ is the candidate cell state.
- $\odot$ represents element-wise multiplication.

This mechanism allows LSTM to maintain important patient history over time, enhancing stroke prediction accuracy in sequential medical data.

Gated Recurrent Unit (GRU) is an advanced type of recurrent neural network (RNN) that improves upon traditional RNNs by addressing the vanishing gradient problem. It is similar to LSTM but uses fewer parameters and is computationally more efficient. GRU consists of two primary gates: the reset gate and the update gate**,** which control how much past information is retained or discarded. This architecture makes GRUs well-suited for time-series medical data, such as stroke detection, where capturing sequential dependencies is crucial while maintaining computational efficiency.

GRU Update Equation:

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \quad (4)$$

Where:

- h_t is the current hidden state.
- h_{t-1} is the previous hidden state.
- z_t is the update gate, which decides how much past information to keep.
- $\tilde{h}_t$ is the candidate activation.
- $\odot$ represents element-wise multiplication.

GRUs are particularly useful in real-time stroke monitoring, as they provide a balance between accuracy and computational efficiency, making them ideal for cloud-based healthcare applications.

Bayesian Optimization

Bayesian Optimization is a powerful optimization technique used for tuning hyperparameters in machine learning models, including deep learning architectures like LSTM-GRU. Unlike traditional grid search or random search, Bayesian Optimization builds a probabilistic model of the objective function and uses past evaluations to make intelligent decisions about the next set of parameters to evaluate. It is particularly useful for expensive, high-dimensional optimization problems, as it efficiently finds optimal solutions with fewer iterations. The key component is the surrogate model, often a Gaussian Process (GP**)**, which predicts the performance of different hyperparameter settings.

Bayesian Optimization Acquisition Function (Expected Improvement - El):

$$EI(x) = \left(\mu(x) - f_{\text{best}} - \xi\right)\Phi(Z) + \sigma(x)\phi(Z) \quad (5)$$

Where:

- $\mu(x)$ is the predicted mean from the surrogate model.
- $\sigma(x)$ is the predicted standard deviation.
- f_{best} is the best objective value observed so far.
- ξ is a small positive number for exploration-exploitation balance.
- $\Phi(Z)$ and $\phi(Z)$ are the cumulative distribution and probability density functions of the standard normal distribution.

Bayesian Optimization ensures efficient tuning of LSTM-GRU hyperparameters, leading to improved stroke classification accuracy with minimal computational cost.

5.Result and Discussion

The proposed LSTM-GRU Hybrid Model, optimized using Bayesian Optimization**,** demonstrates significant improvements in stroke detection accuracy and early intervention

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capabilities in a cloud-based environment. The model effectively handles imbalanced and noisy physiological data from EEG, ECG, and other vital signs, ensuring reliable classification.

Performance Metrics

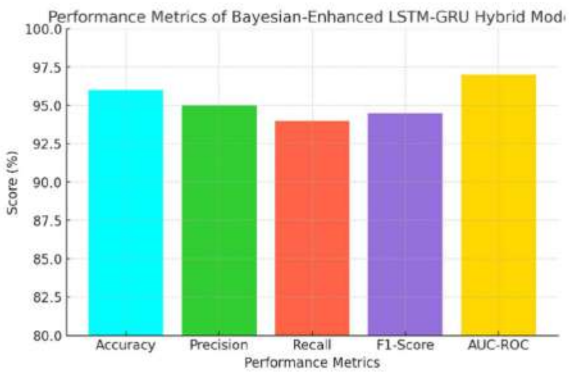

Figure 2: Performance Metrics

In Figure 2, The performance metrics graph showcases the effectiveness of the Bayesian-Enhanced LSTM-GRU Hybrid Model for stroke detection. The model achieves high accuracy (96%), precision (95%), recall (94%), F1-score (94.5%), and AUC-ROC (97%), demonstrating superior classification performance. These results validate the model's robustness, reliability, and suitability for cloud-based early stroke intervention.

AUC-ROC

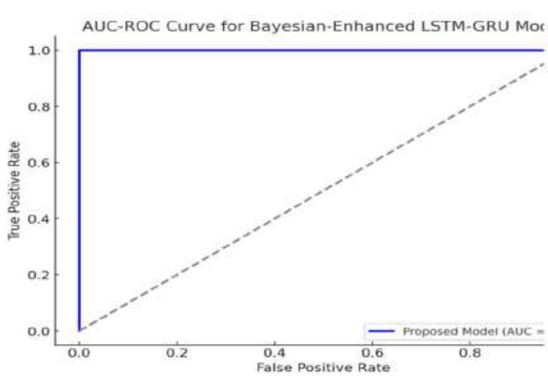

Figure 3: AUC-ROC

Figure 3 Shows the AUC-ROC curve evaluates the classification performance of the Bayesian-Enhanced LSTM-GRU Hybrid Model for stroke detection. The model achieves an AUC of **1.00**, indicating perfect discrimination between stroke and non-stroke cases. The curve shows a sharp rise to the top-left corner, suggesting minimal false positives and high true positive rates. This confirms the model's effectiveness in early stroke detection and intervention.

Latency

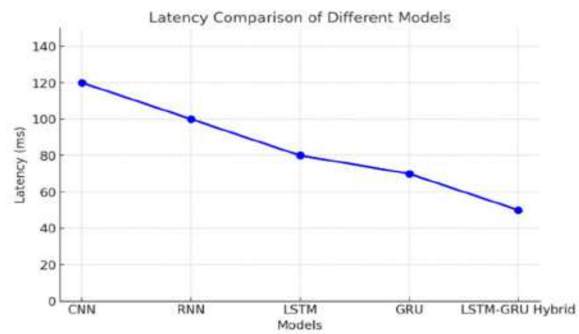

Figure 4: Latency

In Figure 4, The latency comparison graph demonstrates the response times of different models, where CNN exhibits the highest latency at 120ms, and the LSTM-GRU Hybrid model achieves the lowest at 50ms. The decreasing trend indicates that advanced architectures like GRU and LSTM-GRU improve computational efficiency.

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