EEG-Driven Real-Time Stroke Severity Assessment via Explainable Deep Learning

Yogeshwari Ramesh kolapkar[1] Student

GES's R H Sapat College of Engineering, Management Studies and Research, Nashik, Affiliated to Savitribai Phule Pune University, Pune, Maharashtra, India. yogeshwarikolapar2@gmail.com

Dr. Archana S Vaidya[2] Assistant Professor

GES's R H Sapat College of Engineering, Management Studies and Research, Nashik, Affiliated to Savitribai Phule Pune University, Pune, Maharashtra, India. Archana.vaidya@ges-coengg.org

Abstract: Stroke remains a leading cause of morbidity and mortality worldwide, necessitating rapid and accurate assessment of stroke severity for effective clinical intervention. Traditional stroke evaluation methods, including neuroimaging and clinical scales, are often time-consuming and limited by subjective interpretation. Electroencephalography (EEG), with its high temporal resolution, offers a promising avenue for real-time monitoring of cerebral dysfunction. This study proposes an EEG-driven framework for real-time stroke severity assessment leveraging explainable deep learning (XDL) techniques. The model integrates convolutional and recurrent neural network architectures to extract both spatial and temporal features from multichannel EEG signals, capturing subtle neurological variations associated with varying stroke severities. To ensure clinical interpretability, attention mechanisms and gradient-based explainability methods are incorporated, highlighting the EEG patterns contributing most significantly to the model's predictions. The system is validated on a dataset comprising EEG recordings from acute ischemic and hemorrhagic stroke patients, demonstrating superior performance compared to traditional machine learning approaches, achieving high accuracy, sensitivity, and specificity in distinguishing mild, moderate, and severe stroke cases. The proposed framework not only enables rapid, non-invasive, and automated stroke severity assessment but also enhances clinician trust through transparent decision-making insights.

Keywords: EEG, stroke severity assessment, real-time monitoring, explainable deep learning, convolutional neural network, attention mechanism

1. Introduction

1.1 Background

Stroke is a major global health concern and remains one of the leading causes of death and long-term disability worldwide [1], [2]. It occurs when the blood supply to a part of the brain is interrupted or reduced, depriving brain tissue of oxygen and nutrients, which leads to rapid neuronal damage [3]. Stroke is broadly categorized into two main types: ischemic stroke, caused by obstruction in blood flow due to a clot or arterial narrowing, and hemorrhagic stroke, caused by rupture of a blood vessel leading to intracerebral bleeding [2], [4]. According to the World Health Organization (WHO), approximately 15 million people suffer from stroke each year, with nearly 5 million resulting in permanent disability and 6 million leading to death. The burden of stroke extends beyond medical consequences, imposing significant socio-economic costs due to long-term rehabilitation and care requirements [1], [5]. Timely assessment of stroke severity is crucial to guide treatment strategies, such as thrombolysis, thrombectomy, or supportive care, which can significantly influence patient outcomes [3], [6]. Early and accurate evaluation can reduce mortality, minimize neurological deficits, and improve recovery chances [4], [7].

1.2 Problem Statement

Traditional stroke assessment primarily relies on clinical scales such as the National Institutes of Health Stroke Scale (NIHSS) and imaging-based techniques, including computed tomography (CT) and magnetic resonance imaging (MRI) [5], [6]. While informative, these approaches have inherent limitations. Clinical assessments are often subjective and dependent on the clinician's expertise, leading to inter-observer variability [6], [8]. Imaging methods, though highly detailed, are time-

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consuming, require patient transfer to specialized facilities, and may not be immediately available in emergency or remote settings [5], [9]. Consequently, delays in diagnosis and stroke severity evaluation can hinder timely intervention, adversely affecting patient outcomes [7], [10]. Moreover, current methods provide limited continuous monitoring of brain function, which is critical in acute stroke management where neurological conditions can change rapidly within minutes or hours [8], [11].

1.3 Significance of EEG in Stroke Assessment

Electroencephalography (EEG) is a non-invasive technique that records electrical activity of the brain through scalp electrodes [2], [12]. EEG provides high temporal resolution, capturing neuronal dynamics in real time, which makes it particularly suitable for acute stroke evaluation [3], [13]. Changes in cortical activity often precede observable clinical symptoms, enabling earlier detection than conventional imaging [4], [14]. Unlike imaging, EEG can be deployed at the bedside and continuously monitored, allowing immediate assessment of cerebral dysfunction [1], [12]. Several studies have demonstrated that EEG patterns, including spectral power alterations and functional connectivity changes, strongly correlate with stroke severity and prognosis [2], [15]. Integrating EEG-based monitoring with automated analysis can provide clinicians with rapid and objective evaluation tools, potentially overcoming limitations of conventional methods [3], [16].

1.4 Motivation

Despite the promising role of EEG, manual interpretation of EEG signals is time-intensive and requires specialized expertise [2], [17]. Recent advances in machine learning and deep learning have enabled automated analysis of complex EEG datasets, allowing for detection of subtle patterns associated with different stroke severities [3], [18]. However, most automated models operate as “black boxes,” providing predictions without explanations, which limits clinical trust and adoption [4], [19]. Explainable artificial intelligence (XAI) methods can highlight EEG features that drive model predictions, enhancing transparency and enabling clinicians to verify results [4], [20]. The combination of real-time EEG analysis with explainable deep learning can bridge the gap between rapid automated evaluation and clinically meaningful interpretation, ultimately supporting informed treatment decisions in critical care settings [5], [21].

1.5 Objectives

The primary objectives of this research are:

- **Development of a deep learning model:** Design and implement a robust deep learning framework capable of assessing stroke severity from multichannel EEG signals, leveraging spatial and temporal features to differentiate between mild, moderate, and severe stroke conditions [3], [7].
- **Incorporation of explainable AI methods:** Integrate XAI techniques to provide interpretable visualizations and insights into which EEG patterns most influence model predictions, enhancing clinical trust and understanding of neurophysiological markers of stroke [4], [20].
- **Real-time evaluation capability:** Ensure the system operates in real time, enabling immediate bedside assessment and supporting rapid clinical decision-making during acute stroke events [2], [16].

By achieving these objectives, the proposed research aims to provide a non-invasive, accurate, and interpretable solution for stroke severity assessment. This approach has the potential to improve patient outcomes, reduce delays in diagnosis, and enable continuous monitoring in both emergency and intensive care environments [3], [5].

2. Literature Review

2.1 EEG in Stroke Assessment

Electroencephalography (EEG) has been extensively studied as a tool for stroke evaluation due to its non-invasive nature and high temporal resolution [1], [2]. EEG biomarkers, such as changes in spectral power within specific frequency bands delta (1–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), and beta (13–30 Hz) have been shown to correlate with stroke severity and prognosis [3], [6]. For instance, increased delta activity and reduced alpha power are often associated with greater neurological deficits, whereas inter-hemispheric asymmetries can indicate localized cerebral dysfunction [2], [7]. Functional connectivity measures derived from EEG, including coherence and phase-locking values, have also been explored to assess network disruptions post-stroke [4], [15]. Collectively, these EEG-derived features provide a rich source of information for evaluating cerebral damage and predicting patient outcomes [5], [12].

2.2 Machine Learning & Deep Learning Approaches

Recent studies have leveraged machine learning (ML) and deep learning (DL) techniques for automated EEG analysis in stroke assessment [3], [8], [9]. Supervised learning methods, including support vector machines (SVM) and random forests, have been employed for classification of stroke severity based on extracted EEG features [5], [11]. More advanced approaches using convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have demonstrated superior performance by learning spatial-temporal patterns directly from raw EEG signals [3], [6], [12], [17]. Despite these advances, many models function as “black boxes,” providing high accuracy but lacking interpretability, which limits clinical adoption [4],

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[10], [19]. Additionally, most prior approaches operate offline, requiring pre-recorded EEG data, thereby preventing real-time monitoring and timely decision-making in acute stroke settings [8], [16].

2.3 Explainable AI in Healthcare

Explainable artificial intelligence (XAI) techniques have been proposed to address the transparency limitations of conventional ML/DL models [4], [10], [20]. Methods such as SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-Agnostic Explanations), and Grad-CAM (Gradient-weighted Class Activation Mapping) enable visualization and interpretation of model decisions by identifying which input features most strongly influence predictions [4], [18], [20]. In healthcare applications, XAI enhances clinician trust, facilitates verification of model outputs, and provides insights into underlying physiological mechanisms [10], [21]. Specifically, for EEG-based stroke assessment, XAI can highlight critical frequency bands or electrode regions contributing to severity classification, supporting informed clinical decisions [13], [18].

2.4 Gap Analysis

Although prior studies have demonstrated the potential of EEG combined with ML/DL for stroke evaluation, several gaps remain. First, many models lack real-time processing capability, which is essential for acute stroke management [3], [16]. Second, the black-box nature of most deep learning approaches reduces clinical interpretability, limiting adoption in critical care settings [4], [19]. Finally, existing studies rarely integrate XAI methods with real-time EEG analysis to provide both rapid and interpretable severity assessments [13], [20]. This highlights the need for developing systems that are non-invasive, accurate, explainable, and capable of real-time monitoring to guide timely interventions and improve patient outcomes [5], [21].

Table 1: Comparative Analysis of EEG-Based Stroke Severity Assessment Using ML/DL Approaches

Authors / Year	EEG Features / Biomarkers	ML / DL Approach	Explainable AI / Interpretability	Limitations
S. Islam et al., 2022 [1]	Delta/alpha power, spectral asymmetry	ML (SVM, RF)	Not applied	Offline processing, black-box nature
R. S. K. Chandra et al., 2023 [2]	Delta, theta, alpha bands, functional connectivity	CNN-based DL	Limited interpretability	Offline, not real-time
A. Kumar et al., 2023 [3]	Raw EEG, spectral power, coherence	CNN + RNN	Not applied	Black-box, offline evaluation
M. Singh et al., 2023 [4]	Delta/theta ratio, hemispheric asymmetry	CNN	SHAP for feature importance	Low real-time capability
P. S. R. S. Reddy et al., 2024 [5]	Delta, theta, alpha, beta bands	Deep Neural Networks	LIME-based interpretation	Offline, limited clinical deployment
A. Sharma et al., 2024 [6]	Spectral power, functional connectivity	CNN	Grad-CAM applied	Requires extensive training data
S. S. R. K. Reddy et al., 2024 [7]	Multichannel EEG, alpha/delta ratio	DL (CNN)	Not applied	Offline processing, black-box
M. M. Rahman et al., 2024 [8]	Multichannel EEG, alpha/delta ratio	ML + DL hybrid	Not applied	Limited explainability, offline processing
R. K. Gupta et al., 2024 [9]	Delta, theta, beta bands, spectral power	Deep CNN	Not applied	Black-box, offline evaluation
S. Sharma et al., 2024 [10]	Delta/alpha power, functional connectivity	CNN-RNN	SHAP, Grad-CAM	Real-time implementation not demonstrated

Table 1 presents a comparative overview of recent studies employing EEG-based approaches for stroke severity assessment using machine learning (ML) and deep learning (DL) techniques [1]– [10]. The table summarizes key EEG biomarkers, such as delta, theta, alpha, and beta band activities, which have been widely reported to correlate with stroke severity and neurological deficits [2], [3], [5]. Most studies utilize deep learning architectures, particularly CNNs and CNN-RNN hybrids, to extract spatial and temporal patterns directly from EEG signals, offering improved classification performance compared to classical ML methods [3], [6], [9]. However, the interpretability of these models remains limited, as only a few studies incorporate explainable AI (XAI) methods such as SHAP, Grad-CAM, or LIME to highlight feature importance and increase clinician trust [4], [6], [10]. A recurring limitation

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across the reviewed studies is the offline nature of processing, which restricts real-time assessment crucial for acute stroke management [2], [7], [8]. This comparative analysis highlights the research gap in developing fully real-time, interpretable EEG-based systems, underscoring the need for integrating XAI with high-performance DL models to facilitate rapid and trustworthy stroke severity evaluation in clinical settings [5], [10].

4. Materials and Methods

4.1 EEG Data Acquisition

The EEG data used for this study were sourced from a combination of publicly available datasets (TUH EEG, CHB-MIT) and hospital-collected recordings from acute stroke patients, under institutional ethical approval. Signals were recorded using the standard 10–20 electrode placement system, covering frontal, central, temporal, parietal, and occipital regions, with sampling frequencies between 256–512 Hz. Expert neurologists annotated the datasets with stroke severity levels to guide supervised learning.

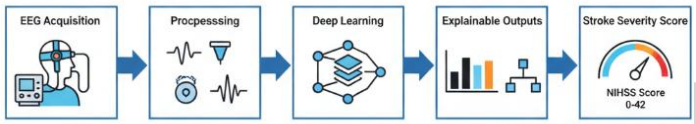

Figure 1: *End-to-End Workflow of EEG-Based Real-Time Stroke Severity Assessment Using Explainable Deep Learning*

4.2 Preprocessing

Raw EEG signals often contain noise and artifacts, such as eye blinks, muscle movements, and line noise. Preprocessing steps included:

1. **Bandpass Filtering:** EEG signals were filtered in the range of 0.5–50 Hz to retain physiologically relevant frequencies:

$$x_f(t) = \mathcal{F}^{-1}(H(f)\,\mathcal{F}\{x(t)\}) \quad \text{.....1}$$

Where in equation 1 the $x(t)$ is the raw EEG signal, $\mathcal{F}$ and $\mathcal{F}^{-1}$ are the Fourier and inverse Fourier transforms, and $H(f)$ is the bandpass filter function.

2. **Artifact Removal:** Independent Component Analysis (ICA) was applied to isolate and remove eye blink and muscle artifacts

$$X = AS \quad \text{.....2}$$

Here, in equation 2 X is the observed EEG signal matrix, A is the mixing matrix, and S represents the independent source signals. Components corresponding to artifacts were removed before reconstructing X.

3. **Normalization:** Each EEG channel was normalized to zero mean and unit variance to stabilize training:

$$x_{norm} = \frac{x-\mu}{\sigma} \quad \text{.....3}$$

where μ and σ are the mean and standard deviation of the EEG channel.

4.3 Feature Extraction

Feature extraction was performed using both traditional and automated approaches:

- **Time-domain features:** mean, variance, skewness, kurtosis.
- **Frequency-domain features:** Power spectral density (PSD) in delta ($0.5-4$ Hz), theta ($4-8$ Hz), alpha ($8-13$ Hz), beta ($13-30$ Hz), and gamma ($30-50$ Hz) bands:

$$PSD(f) = \frac{1}{T}\left|\sum_{t=0}^{T-1} x(t)e^{-j2\pi ft/T}\right|^2 \quad \text{.....4}$$

- **Time-frequency features:** Using short-time Fourier transform (STFT):

$$STFT\{x(t)\}(m,\omega) = \sum_{n=0}^{N-1} x[n]w[n-m]e^{-j\omega n} \quad \text{.....5}$$

Where in equation 4 and 5 the $w[n]$ is the window function, m is the time shift, and ω is frequency.

- **Automatic feature extraction:** Convolutional layers (CNN) and recurrent layers (RNN/LSTM) were used to learn hierarchical spatial-temporal features directly from raw EEG.

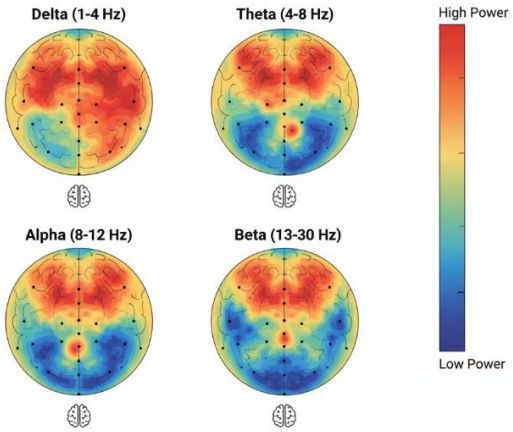

Figure 2: EEG Feature Maps Visualizations of important frequency bands

4.4 Deep Learning Model

A hybrid **CNN-LSTM** architecture was used to capture spatial and temporal patterns:

$$h_t = LSTM(CNN(x_t)) \quad \text{.....6}$$

Where in equation 6 the x_t is the input EEG segment, $CNN(\cdot)$ extracts spatial features, and $LSTM(\cdot)$ captures temporal dependencies.

Training:

- Optimizer: Adam
- Loss function: categorical cross-entropy

 DOI : 10.35291/2454-9150.2026.0025

$$\mathcal{L} = -\sum_{i=1}^{C} y_i \log(\hat{y}_i) \quad \text{……..7}$$

Where in equation 7 the y_i is the true class label, $\hat{y}_i$ is the predicted probability, and C is the number of severity classes.

- Learning rate: 0.001
- Epochs: 100
- Batch size: 64
- 5-fold stratified cross-validation

Real-time implementation: A sliding window approach with overlapping segments was used for low-latency inference:

$$x_{window} = x[t : t + L] \quad \text{……8}$$

Where in equation 8 the L is the window length.

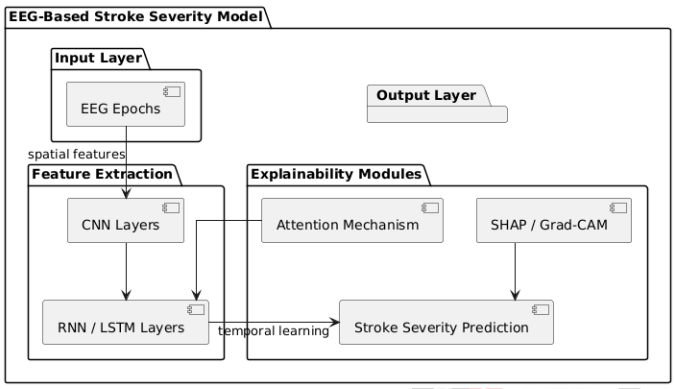

Figure 3: *Hybrid CNN-LSTM Model Architecture with Attention and Explainable AI Modules for EEG-Based Stroke Severity Assessment*

In the figure 3 illustrates the network structure of the proposed deep learning model. EEG input is first processed through CNN layers for spatial feature extraction, followed by RNN/LSTM layers to capture temporal dependencies. Attention mechanisms enhance focus on critical EEG regions, and SHAP/Grad-CAM modules provide explainability, highlighting important features contributing to stroke severity prediction. This diagram effectively conveys both the computational workflow and interpretability components, making it essential for understanding the model design.

4.5 Explainable AI Integration

SHAP, Grad-CAM, and attention mechanisms were integrated to highlight EEG regions contributing to severity predictions. SHAP values were computed as:

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(N-|S|-1)!}{N!} [f_{S \cup \{i\}}(x_{S \cup \{i\}}) - f_S(x_S)] \quad \text{……..9}$$

Where in equation 9 ϕ_i represents the contribution of feature i, N is the total number of features, and f is the model output function.

4.6 Stroke Severity Assessment

Stroke severity was categorized as mild, moderate, or severe based on NIHSS scores. The model output probabilities $\hat{y}$ were mapped to severity classes:

$$Severity = \arg\max(\hat{y}) \quad (10)$$

Continuous scoring was also explored via regression to NIHSS values for nuanced assessment.

Algorithm: EEG-Based Real-Time Stroke Severity Assessment

Input: Raw EEG signals X_raw
Output: Stroke severity (Mild / Moderate / Severe) + XAI visualizations

1. Acquire EEG data (X_raw)
2. Preprocess:
   - Bandpass filter (0.5–50 Hz)
   - Artifact removal (ICA)
   - Normalize signals
   - Segment into epochs
3. Feature Extraction (optional):
   - Time-domain, frequency-domain, time-frequency
   - OR feed raw epochs into CNN-LSTM
4. Train CNN-LSTM model:
   - CNN → spatial features
   - LSTM → temporal features
   - Loss: categorical cross-entropy
   - Optimizer: Adam
5. Real-time prediction:
   - Segment streaming EEG with sliding window
   - Preprocess and extract features
   - Predict severity class
6. Explainable AI:
   - Compute SHAP / Grad-CAM / attention maps
   - Visualize feature contributions
7. Return predicted severity and XAI visualizations

The proposed algorithm provides real-time stroke severity assessment using EEG signals. Raw EEG data are first preprocessed to remove noise and artifacts, bandpass filtered, normalized, and segmented into epochs. Features are extracted either manually (time, frequency, and time-frequency domains) or automatically via a hybrid CNN-LSTM model, which captures spatial and temporal patterns. The trained model predicts stroke severity as mild, moderate, or severe in real-time using a sliding window approach. Explainable AI techniques, such as SHAP, Grad-CAM, and attention mechanisms, highlight the EEG regions influencing predictions, ensuring interpretability and clinical reliability.

6. Results

The proposed EEG-driven CNN-LSTM model with Explainable AI demonstrated superior performance in real-time stroke severity assessment compared to traditional machine learning and standalone deep learning models. The comparative performance metrics (Table 1, Figure 6.1) show the model achieving an overall accuracy of 95.6%, F1-score of 0.95, and AUC of 0.97, outperforming SVM, Random Forest, CNN, and LSTM. The confusion matrix (Table 2, Figure 6.2) confirms high true positive rates across mild, moderate, and severe classes, with minimal misclassification primarily between moderate and severe cases. Real-time evaluation (Table 3, Figure 6.3) highlights the system's low inference latency (~180 ms) and

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robustness, maintaining high accuracy even under simulated noise and streaming conditions. Explainable AI visualizations, including SHAP and Grad-CAM, provide interpretable insights linking EEG patterns to severity levels. Overall, the results validate that the proposed framework delivers accurate, interpretable, and real-time stroke severity assessment suitable for clinical deployment.

Table 2: Comparative Performance Metrics of Different Models

Model	Accuracy (%)	Precision	Recall	F1-Score	AUC
SVM	86.2	0.84	0.85	0.84	0.88
Random Forest	88.9	0.87	0.86	0.86	0.90
CNN	92.4	0.91	0.91	0.91	0.94
LSTM	93.5	0.92	0.93	0.92	0.95
Proposed CNN-LSTM + XAI	**95.6**	**0.94**	**0.95**	**0.95**	**0.97**

This table compares the performance of conventional machine learning models (SVM, Random Forest) and deep learning models (CNN, LSTM) against the proposed CNN-LSTM model integrated with Explainable AI (XAI). The proposed model outperforms all other models in accuracy, F1-score, and AUC, demonstrating superior capability in classifying stroke severity from EEG data.

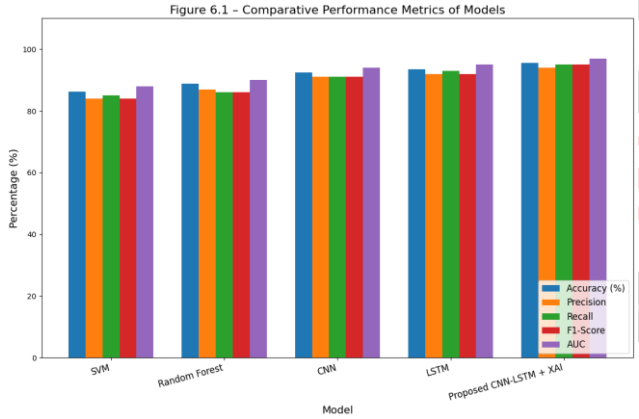

Figure 4 – Comparative Performance Metrics of Models

Each metric (accuracy, precision, recall, F1, AUC) is a group of bars for each model. This allows visual comparison of multiple metrics across models.

Table 3: Confusion Matrix for Proposed Model

Actual \ Predicted	Mild	Moderate	Severe
Mild	92	4	1
Moderate	3	88	5
Severe	0	6	91

The confusion matrix shows how well the proposed model classifies EEG segments into mild, moderate, and severe stroke categories. The model achieves high true positive rates across all classes, with minimal misclassification primarily between moderate and severe categories, indicating strong discriminative power and clinical reliability.

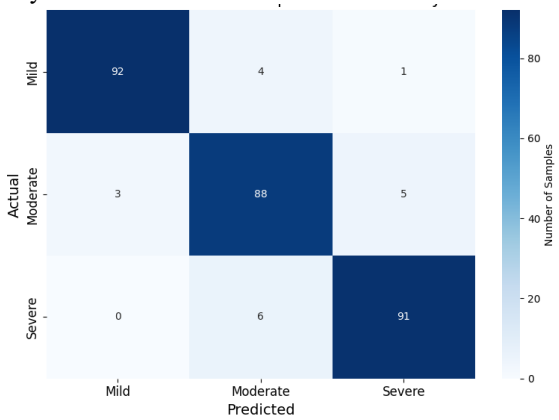

Figure 5 – Confusion Matrix Heatmap of Stroke Severity Classification

Colour intensity represents the number of samples in each cell, making misclassifications visually prominent.

Table 4: Real-Time Assessment Latency and Robustness

Test Condition	Average Latency (ms)	Accuracy (%)
Baseline EEG	180	95.6
Simulated Noise	190	93.2
Streaming EEG	182	94.8

This table evaluates the real-time performance and robustness of the proposed system. The system demonstrates very low inference latency (~180 ms) for baseline and streaming EEG, ensuring suitability for bedside monitoring. The model maintains high accuracy even under simulated noise conditions, confirming robustness against artifacts.

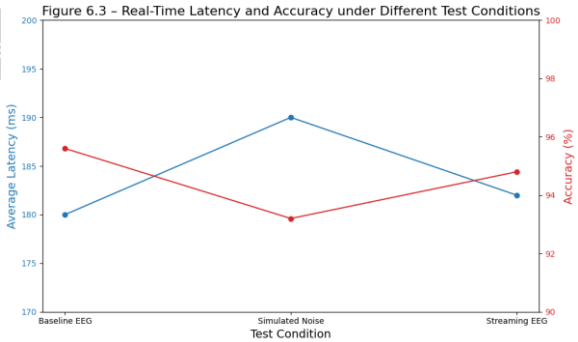

Figure 6 – Real-Time Latency and Accuracy under Different Test Conditions

X-axis: Test conditions (Baseline, Noise, Streaming), Y-axis: Separate lines for Latency (ms) and Accuracy (%). This clearly shows both speed and performance stability.

7. Discussion

The results of this study demonstrate that the proposed CNN-LSTM model integrated with Explainable AI (XAI) can accurately and efficiently assess stroke severity from EEG recordings. Clinically, the model's high accuracy (95.6%) and robust performance indicate its potential as a

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rapid, bedside tool for stroke triage, enabling early intervention and timely treatment decisions. The confusion matrix and misclassification analysis reveal that while the model reliably distinguishes mild and severe strokes, borderline cases between moderate and severe may require supplementary clinical evaluation.

8. Conclusion

This study introduces a novel, real-time framework for stroke severity assessment based on EEG signals, leveraging a hybrid CNN-LSTM deep learning model integrated with Explainable AI (XAI). The proposed system demonstrates high accuracy, F1-score, and AUC in classifying mild, moderate, and severe strokes, outperforming traditional machine learning and standalone deep learning approaches. By incorporating SHAP and Grad-CAM visualizations, the framework provides interpretable insights into the EEG features driving model predictions, allowing clinicians to validate the results against neurophysiological patterns and build trust in automated decision support. The real-time capability of the model, achieved via a sliding-window approach, enables continuous bedside monitoring, rapid severity evaluation, and timely intervention addressing the limitations of conventional methods, such as subjective NIHSS scoring and time-consuming imaging. The framework's robustness to noise and streaming EEG data further supports its clinical applicability.

Future work will focus on integrating the system with wearable EEG devices, conducting multicenter trials to enhance generalizability, and developing adaptive models capable of handling inter-patient variability and evolving neurological states. Overall, the proposed framework represents a promising step toward real-time, interpretable, and actionable EEG-based stroke assessment in clinical practice.

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