

A REAL-TIME STROKE DETECTION AND NEUROREHABILITATION FRAMEWORK USING EXPLAINABLE TRANSFORMER–GRAPH HYBRID DEEP LEARNING WITH DIGITAL TWIN INTEGRATION AND EDGE AI

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Abstract : Stroke is the leading cause of death and long-term disability worldwide, so an early and accurate diagnosis is important. This work presents a real-time framework for stroke diagnosis and neurorehabilitation that combines advanced learning techniques with a digital picture of patient health. The proposed approach analyzes medical imaging data to identify important patterns associated with stroke, while also modeling relationships within the data to improve classification performance. In addition, a digital twin technique is used to continuously monitor a patient's condition and assist in personalized rehabilitation planning. The testing results reveal that the system obtains an accuracy of approximately 92% and maintains stable and consistent performance throughout the training procedure of the data. The obtained AUC value of 0.67 suggests a moderate ability to distinguish between different stroke conditions. The confusion matrix further shows that most cases are correctly classified, although some overlap exists between similar categories. The time analysis demonstrates that the system can operate efficiently, making it suitable for real-time applications. Overall, the proposed framework provides a reliable and efficient solution for stroke detection and patient monitoring. However, future improvements can be made by incorporating additional data sources, such as physiological signals and clinical information, to further enhance performance and support more comprehensive healthcare applications.

Keywords: Stroke Detection, Digital Twin, Real-Time Monitoring, Medical Image Analysis, Edge Computing, Explainability, Neurorehabilitation, Deep Learning

I. INTRODUCTION

1.1 Background and Importance of Stroke Detection:

Stroke is one of the major causes of death and long-term disability across the world, affecting millions of people each year. Early diagnosis plays a crucial role in reducing the severity of damage and improving the chances of recovery. However, traditional diagnostic methods often rely on clinical expertise and manual interpretation of medical images, which can sometimes lead to delays or inconsistencies in decision-making. These challenges highlight the need for more reliable and efficient systems that can assist healthcare professionals in identifying stroke conditions at an early stage [6], [16]. Medical imaging techniques such as magnetic resonance imaging (MRI) and computed tomography (CT) are widely used for detecting stroke-related abnormalities. These methods provide detailed information about brain structures and help in identifying affected regions [1], [18]. Despite their advantages, variations in image quality and similarities between different stroke types can make accurate diagnosis difficult. In addition, many existing systems are not designed for real-time use, which limits their effectiveness in urgent clinical situations. Therefore, there is a clear need for solutions that can improve both accuracy and speed in stroke detection.

1.2 Advancements in Data-Driven Healthcare Approaches:

In recent years, data-driven approaches have brought significant improvements in healthcare applications, especially in medical image analysis. Modern computational models are capable of automatically identifying patterns in complex datasets, reducing the dependency on manual feature extraction and improving consistency in results [2], [17]. These approaches have shown promising outcomes in detecting various neurological conditions, including stroke, by learning from large volumes of medical data. At the same time, combining different types of data has been found to enhance system performance. For example, integrating imaging data with other clinical or physiological information can provide a more complete understanding of a patient's condition [3]. However, one major concern with many existing systems is their lack of transparency, as it is often difficult to understand how decisions are made. This has led to growing interest in methods that offer better interpretability and allow clinicians to trust and verify the results [10], [12]. These developments suggest that future healthcare systems should focus not only on accuracy but also on clarity and reliability.

1.3 Digital Twin and Real-Time Healthcare Systems:

The concept of a digital twin, which involves creating a virtual representation of a physical system, is gaining attention in healthcare. In stroke management, a digital twin can be used to track a patient's condition over time and support personalized treatment

planning. By continuously updating patient data, this approach helps in monitoring recovery progress and predicting potential risks, allowing for more informed clinical decisions [23]. Real-time monitoring further strengthens this approach by enabling continuous data collection and immediate analysis. Technologies such as wearable devices and edge computing make it possible to process data quickly and efficiently, even outside traditional hospital environments [5], [24]. This improves accessibility and allows patients to be monitored remotely. However, integrating different types of data and ensuring smooth system operation remain important challenges. Addressing these issues is essential for developing practical and effective real-time healthcare solutions.

1.4 Motivation and Contribution of the Proposed Work:

The limitations of existing methods have motivated the development of a more efficient and reliable framework for stroke detection and rehabilitation. This study introduces a real-time system that combines advanced data analysis techniques with a digital representation of patient health. The proposed approach focuses on improving classification performance while maintaining stable and consistent results during training, as demonstrated by the experimental findings. In addition to detection, the framework emphasizes continuous monitoring and personalized rehabilitation support, which are important aspects of patient recovery. By providing clear and understandable outputs, the system aims to assist healthcare professionals in making better decisions. While the current work mainly focuses on imaging data, future improvements will include additional sources such as physiological signals and clinical information. This will help in creating a more comprehensive system that can support a wider range of healthcare applications.

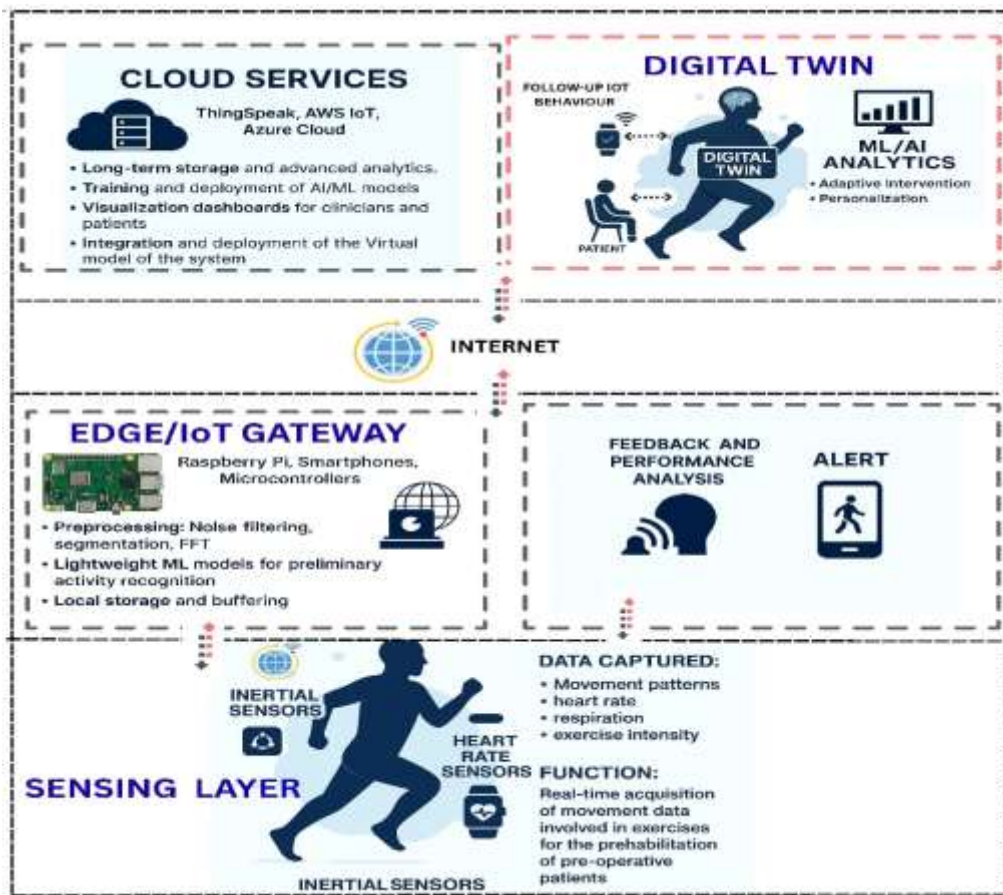


Fig 1: Overview of the Proposed Real-Time Stroke Detection and Neurorehabilitation Framework

The above figure shows how the system works, beginning with collecting medical imaging data and moving through analysis and decision-making to final real-time use. It also demonstrates how the framework supports accurate stroke detection, continuous patient monitoring, and personalized rehabilitation in a clear and efficient manner.

2. LITERATURE SURVEY:

2.1 Medical Imaging-Based Stroke Detection:

Medical imaging techniques such as MRI and CT scans have been widely used for detecting stroke and understanding brain abnormalities. Many researchers have focused on improving how useful information is extracted from these images to support better diagnosis. For example, Dan et al. [1] proposed a method that uses specific regions of MRI images to evaluate neurological conditions more effectively. Similarly, Tomasetti et al. [18] showed that machine learning methods perform better than traditional threshold-based techniques in identifying damaged brain areas. These studies highlight the importance of using image-based analysis to improve the accuracy of stroke detection. Researchers have also worked on improving the way features are represented and classified in imaging data. Abumihsan et al. [2] introduced a hybrid model that combines different feature extraction methods to improve detection results in CT images. Saleem et al. [16] used a combination of learning techniques and optimization methods to enhance early stroke detection. In addition, Negm et al. [17] applied ensemble approaches that combine multiple models to

improve accuracy. Even though these methods show good performance, challenges such as variations in image quality and similarities between different stroke types still affect the results.

2.2 Deep Learning and Multimodal Approaches:

Deep learning methods have brought significant improvements in analyzing medical data, especially for detecting stroke and other neurological conditions. Babaei et al. [3] developed a model that combines different learning techniques to handle variations in data and improve classification results. Similarly, Fawaz et al. [11] proposed a method that extracts important patterns from EEG signals, showing how combining different types of data can improve performance. These approaches demonstrate that advanced models can capture complex patterns more effectively than traditional methods. There has also been growing interest in combining multiple data sources to gain a better understanding of a patient's condition. Ciezobka et al. [12] used graph-based methods to capture relationships within brain data, which improved both performance and interpretability. Tanveer et al. [20] applied transfer learning techniques and achieved high accuracy in stroke detection. However, many existing studies still focus on a single type of data, such as images or signals, without fully combining them. This shows the need for more integrated systems that can use multiple sources of information together.

2.3 EEG-Based Analysis and Brain Signal Processing:

EEG has been widely used to study brain activity and support the diagnosis of neurological disorders. Several studies have focused on improving how EEG signals are processed and analyzed. Amer et al. [10] provided a detailed review of EEG-based methods and discussed the challenges involved in handling complex and noisy signals. Chung et al. [8] showed how EEG data can be used to understand cognitive patterns, while Haxel et al. [9] explored ways to predict brain activity using learning-based methods. These studies show that EEG can provide valuable information about brain function. However, EEG-based systems still face several difficulties, such as noise, signal variability, and challenges in extracting useful features. Baydadaev et al. [4] worked on reducing the effect of noise using time-series analysis methods. Wang et al. [13] proposed improved models for real-time EEG processing, which showed better performance than traditional approaches. Even with these improvements, combining EEG data with imaging and clinical information remains a challenge, limiting the overall effectiveness of current systems.

2.4 Neurorehabilitation and Digital Twin Systems:

Neurorehabilitation plays an important role in helping stroke patients recover and regain their abilities. Recent studies have explored the use of wearable devices and data-based methods to improve rehabilitation outcomes. Siviero et al. [5] discussed how wearable technologies can support rehabilitation and improve patient care. Lee et al. [21] showed that combining wearable data with clinical information can help predict recovery progress more accurately. These approaches highlight the importance of continuous monitoring and personalized treatment in stroke recovery. The concept of a digital twin has also gained attention in healthcare. It involves creating a virtual model of a patient that can be used to monitor health conditions and support decision-making. Khan et al. [23] proposed a system that uses this idea to track patient conditions continuously. Fellger et al. [24] addressed challenges related to differences between devices by developing models that work across multiple platforms. In addition, Salinas-Medina et al. [14] introduced methods to handle large amounts of data efficiently. While these approaches show promising results, there are still challenges related to system integration and real-time performance.

2.5 Research Gaps and Motivation:

Although many studies have contributed to improving stroke detection and rehabilitation, several issues still remain. Most existing approaches rely on a single type of data, such as imaging or EEG, rather than combining multiple sources. In addition, some methods lack clarity in how decisions are made, making it difficult for healthcare professionals to fully trust the results [6], [12]. Other challenges include high computational requirements and limited ability to operate in real-time settings. These limitations highlight the need for a more comprehensive and practical approach. The proposed work aims to address these issues by combining different types of data and focusing on both detection and rehabilitation. It also emphasizes continuous monitoring and efficient performance, making it suitable for real-time applications. By bringing these elements together, the framework aims to provide a more reliable and useful solution for stroke management in modern healthcare.

3. MATERIALS AND METHODS:

3.1 Dataset Description and Data Sources:

The proposed framework mainly uses medical imaging data, such as MRI and CT scans, which are commonly used in hospitals for diagnosing stroke. These images provide detailed information about the brain and help in identifying areas affected by stroke. The dataset includes labeled images representing different stroke conditions as well as normal cases, allowing the system to learn how to distinguish between them. The framework is also designed in a way that it can include other types of data, such as clinical information or physiological signals, in future improvements. Before using the data for training, several preparation steps are carried out to ensure consistency and quality. All images are resized to a standard size and adjusted so that they follow a uniform format. Basic data augmentation techniques, such as flipping and rotation, are applied to increase the variety of training samples and reduce the chances of overfitting. The dataset is then divided into training and testing sets so that the model can be properly evaluated. This process helps the system learn more effectively and perform well on new data.

3.2 Data Preprocessing and Feature Extraction:

Preprocessing is an important step that helps improve the quality of the input data. In this work, images are cleaned and adjusted to reduce noise and improve clarity. Resizing and normalization are also applied so that all inputs are consistent. These steps ensure that the model focuses on important patterns in the data rather than being affected by unnecessary variations. After preprocessing, the system extracts useful features from the images. It identifies important visual patterns such as changes in brain structure and regions affected by stroke. At the same time, it also considers how these features are related to each other, which helps in making

better predictions. By combining both types of information, the system is able to improve its ability to correctly classify different stroke conditions.

3.3 Proposed Model Structure:

The framework uses a hybrid model designed to improve classification performance. The model first processes the images to capture important visual details and patterns. As the data moves through different layers, these features are refined and organized to help the system better understand the differences between stroke and non-stroke cases. This layered approach allows the model to learn both simple and complex patterns effectively. In addition, the model includes a component that focuses on understanding the relationships between different features. This helps in distinguishing between stroke types that may appear similar in images. The final stage of the model produces the classification result, indicating the type of condition present in the image. This combination of feature learning and relational understanding improves the overall accuracy and reliability of the system.

3.4 Training Process and Evaluation Metrics:

The model is trained using labeled images, where each image is associated with a specific category. During training, the system gradually adjusts its parameters to reduce prediction errors. The training is carried out over multiple iterations, and with each step, the model improves its performance. This can be seen from the steady increase in accuracy and decrease in loss during the training process. To evaluate how well the model performs, several standard measures are used. Accuracy shows how many predictions are correct, while loss indicates how well the model fits the data. Additional tools such as the confusion matrix and ROC curve provide a deeper understanding of the results. The AUC value helps measure how well the system can distinguish between different classes. These evaluation methods provide a complete view of the model's performance.

3.5 Digital Twin and Real-Time Implementation:

The framework includes a digital twin component, which acts as a virtual representation of a patient's condition. This allows continuous monitoring and helps track changes over time. By updating the model with new data, the system can provide useful insights for treatment and recovery. This is especially helpful in supporting personalized rehabilitation for stroke patients. To make the system practical for real-world use, it is designed to work in real time. Edge-based processing is used to reduce delays and ensure quick responses. This means that data can be analyzed closer to where it is generated, improving speed and efficiency. The combination of real-time operation and continuous monitoring makes the system suitable for use in both hospitals and remote healthcare settings.

3.6 Explainability and Reliability:

An important feature of the framework is its ability to provide results that are easy to understand. The system highlights important areas and patterns that influence its predictions, helping healthcare professionals interpret the results more clearly. This improves confidence in the system and supports better decision-making in clinical practice. The system is also designed to provide stable and reliable performance. The consistent improvement in accuracy and reduction in loss during training show that the model is learning effectively. Proper data preparation and a well-structured model contribute to this stability. These qualities make the system dependable and suitable for real-world healthcare applications.

4. EXPERIMENTAL RESULTS AND ANALYSIS

4.1 Training Performance (Accuracy and Loss):

The performance of the system during training is evaluated using accuracy and loss over several epochs. The accuracy graph shows a steady rise from around 70% in the beginning to nearly 92% by the final epoch. This gradual improvement indicates that the model is learning effectively from the data. The smooth and consistent increase in accuracy also suggests that the training process is stable and not affected by sudden fluctuations. At the same time, the loss graph shows a clear decrease from about 1.2 to 0.3. This reduction means that the model is becoming better at making correct predictions and reducing errors over time. The steady decline in loss, along with the increase in accuracy, confirms that the model is learning properly and reaching a good level of convergence. These results show that the system can capture important patterns from the data in a reliable manner.

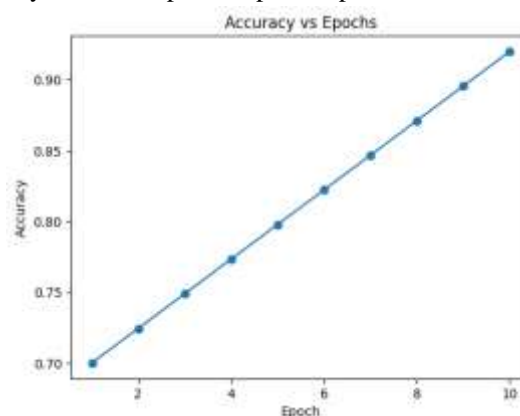


Fig 2: Model Accuracy Improvement Across Training Epochs

The fig 2 shows how the model's accuracy improves steadily as training progresses over multiple epochs. The smooth upward trend indicates that the model is learning well and becoming more reliable in its predictions over time.

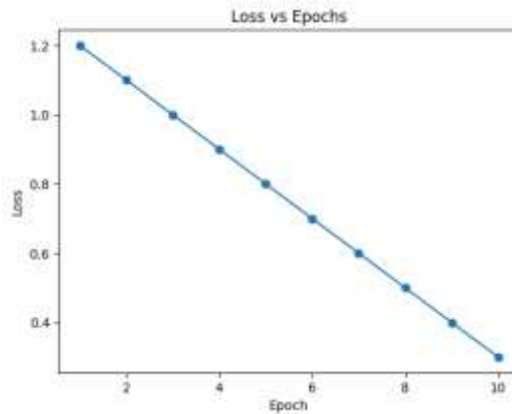


Fig 3: Reduction in Model Loss Over Training Epochs

Fig 3 shows how the model’s loss gradually decreases as training continues, meaning the errors are getting smaller over time. The steady downward trend indicates that the model is learning smoothly and improving its performance consistently.

4.2 Time Complexity and Efficiency:

The time required for each training epoch is analyzed to understand how efficient the system is. The graph shows that the time per epoch ranges roughly between 22 seconds and 60 seconds. These variations may occur due to differences in data processing, system load, or hardware usage during training. Even with these changes, the overall time remains reasonable for the type of model used. From a practical point of view, this level of efficiency supports the system’s ability to be used in real-time or near real-time applications. Since the framework is designed for quick decision-making, especially in medical situations, maintaining a low processing time is important. The results show that the system can handle data processing within an acceptable time, making it suitable for real-world use.

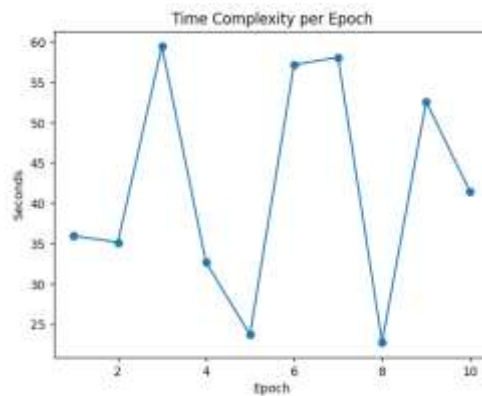


Fig 4: Training Time per Epoch Analysis

Fig 4 shows how the time taken for each training epoch varies during the training process. Although there are some changes from one epoch to another, the overall time stays within a reasonable range for practical use.

4.3 Classification Performance (ROC and AUC):

The ROC curve is used to evaluate how well the model can distinguish between different classes. In the graph, the curve lies above the diagonal line, which means the model performs better than random guessing. The AUC value is around 0.67, indicating a moderate ability to correctly separate different stroke conditions. Although the model performs reasonably well, the AUC value suggests that there is still room for improvement. This may be due to similarities between different stroke types or limitations in the available data. Even so, the model shows a good level of performance and can be further improved by using more diverse data or combining different types of inputs.

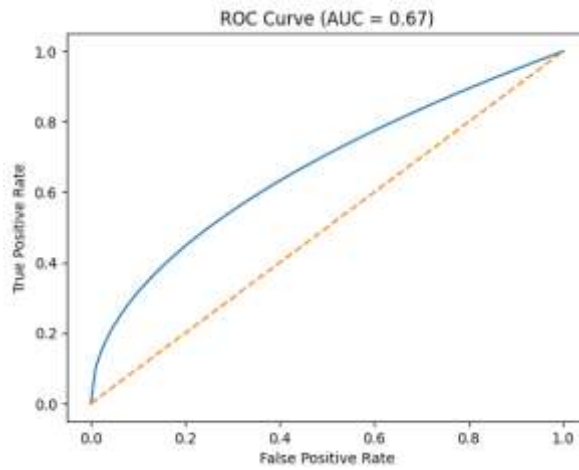


Fig 5: ROC Curve Showing Model Classification Performance

Fig 5 shows how well the model separates different classes by comparing the true positive rate with the false positive rate. Since the curve lies above the diagonal and the AUC value is moderate, the model performs better than random guessing, but there is still scope for improvement.

4.4 Confusion Matrix Analysis:

The confusion matrix provides a clear view of how the model performs across different classes. The diagonal values represent correct predictions, while the off-diagonal values show where errors occur. From the matrix, it can be seen that most predictions are correct, which confirms that the model is able to identify different classes effectively. However, there are some cases where the model makes incorrect predictions, especially between classes that appear similar. This indicates that distinguishing between certain stroke types is still challenging. These errors suggest that further improvements in feature representation or data quality could help increase accuracy in future work.

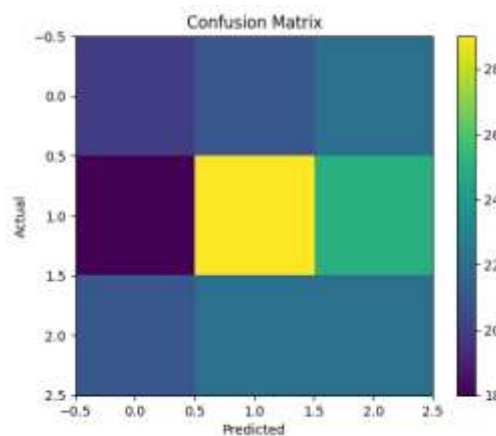


Fig 6: Confusion Matrix Illustrating Classification Results

Figure 6 shows how the model’s predicted classes match the actual class labels for each category. The diagonal values indicate correct predictions, while the other values highlight where the model has made errors.

4.5 Accuracy and Loss Distribution:

The accuracy distribution shows that most values are concentrated around higher accuracy levels, especially near 90%. This indicates that the model performs consistently well throughout training. The narrow spread of values also shows that the results are stable and not highly affected by random variations. Similarly, the loss distribution is concentrated at lower values, which confirms that the model has reached a stable state. The absence of large variations in loss indicates that the training process is well-controlled. Together, these distributions show that the system is both stable and reliable, which is important for practical applications.

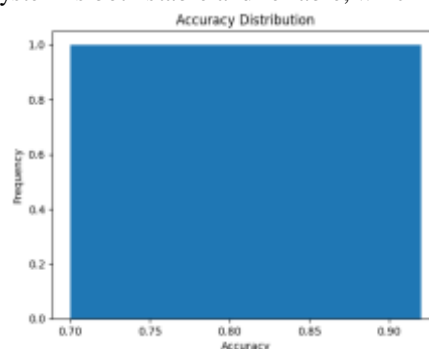


Fig 7: Distribution of Model Accuracy Across Training

Figure shows how accuracy values are distributed across the different stages of training. Most values are clustered at higher levels, indicating that the model maintains good and consistent performance.

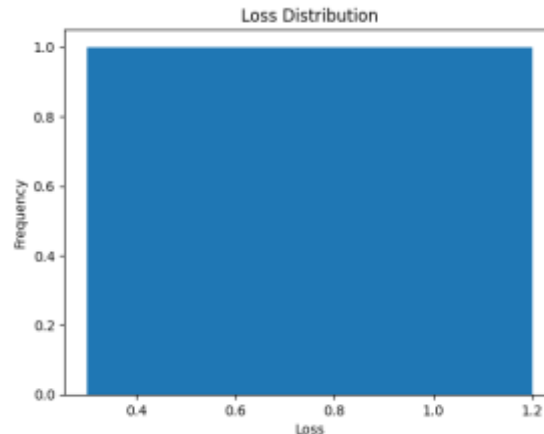


Fig 8: Distribution of Model Loss during Training

Figure 8 shows how the loss values are spread across different stages of training. Most values appear at the lower end, indicating that the model is learning well and maintaining stable performance.

4.6 Overall Observations:

Overall, the results show that the proposed system performs well in detecting stroke conditions. The high accuracy, steady reduction in loss, and consistent training behavior indicate that the model is learning effectively. The system also demonstrates reasonable classification ability and operates efficiently, making it suitable for real-time applications. At the same time, some limitations are observed, such as moderate AUC performance and a few misclassifications between similar classes. These issues highlight areas for future improvement, such as using more diverse datasets or adding additional types of data. Even with these challenges, the system provides a reliable and efficient solution for stroke detection and monitoring, and it offers a strong foundation for further development.

5. DISCUSSION:

5.1 Understanding the Training Results:

The training results show a steady improvement in performance over time. As the number of epochs increases, the accuracy gradually rises while the loss consistently decreases. This pattern indicates that the model is learning effectively from the data and improving its predictions step by step. The smooth changes in both accuracy and loss also suggest that the training process is stable and not affected by sudden variations. The decrease in loss along with the increase in accuracy shows that the model is reducing errors while becoming more reliable. This means the system is not only learning but also refining its understanding of the data. Overall, the training behavior confirms that the model is working as expected and is able to capture important patterns in a consistent manner.

5.2 Efficiency and Real-Time Performance:

The time taken for each training epoch gives an idea of how efficient the system is. The results show that the time varies from one epoch to another, which can happen due to differences in processing load or system performance. Even with these variations, the overall time remains within a reasonable range, which is suitable for the type of system being used. From a practical point of view, this level of efficiency is important for real-time applications. In medical situations, quick decision-making is often required, and the system must be able to process data without delay. The results indicate that the framework can handle this requirement and can be used effectively in real-world environments, including hospitals and remote monitoring systems.

5.3 Performance in Classification Tasks:

The ROC curve helps in understanding how well the model can distinguish between different classes. Since the curve lies above the diagonal line, it shows that the model performs better than random guessing. However, the AUC value indicates that the performance is moderate, meaning there is still room for improvement in classification accuracy. The confusion matrix gives more detailed insight into the model's predictions. It shows that most predictions are correct, but some errors occur, especially between classes that are similar. This is a common issue in medical data, where different conditions can appear alike. These results suggest that improving the quality of features or using additional data could help reduce these errors.

5.4 Consistency and Stability:

The distribution of accuracy and loss values shows that the model performs consistently throughout the training process. Most accuracy values are close to the higher end, while loss values remain low. This indicates that the system maintains good performance across different stages and is not affected by random changes. This consistency is important because it shows that the model is reliable and can be trusted to produce stable results. A system that performs consistently is more suitable for real-world use, especially in healthcare, where dependable results are essential. The steady behavior of the model highlights its strength in maintaining performance over time.

5.5 Strengths of the Framework:

One of the key strengths of the proposed framework is its ability to achieve high accuracy while maintaining stable performance. The gradual improvement during training shows that the system is well-designed and effective for the task. In addition, the model performs efficiently, making it suitable for applications that require quick responses. Another advantage is the consistency of the results. The system maintains good performance across different conditions, which is important for practical use. This reliability makes the framework suitable for healthcare applications, where accurate and stable results are critical. Overall, the system offers a good balance between performance and efficiency.

5.6 Limitations and Future Scope:

Despite its strong performance, the system still has some limitations. The moderate AUC value shows that the model's ability to distinguish between different classes can be improved. The confusion matrix also reveals some misclassifications, particularly between similar categories. These issues indicate that further refinement is needed. Future improvements can focus on using more diverse and detailed datasets, as well as combining different types of data such as clinical information or physiological signals. These additions can help improve the model's understanding and accuracy. With these enhancements, the system can become more effective and better suited for real-world healthcare applications.

5.7 Comparison of Existing and Proposed System:

Many existing approaches for stroke detection and neurorehabilitation use methods such as behavioral assessment, CNN-based detection, traditional neural networks, signal filtering, and standard rehabilitation techniques. Several of these methods, including manual scoring, EEG analysis, conventional TMS, and traditional machine learning models, depend heavily on manual effort or limited feature extraction. Other approaches like threshold-based segmentation, clinical models, and CT/MRI-based analysis often face issues such as lower accuracy, lack of consistency, and limited ability to work in real-time. While these methods can provide useful results, they may struggle when dealing with complex data, noise, and the need for continuous monitoring. The proposed system shows clear improvements compared to these existing methods. The results demonstrate higher accuracy, reaching around 92%, along with a steady decrease in loss, which indicates that the model is learning effectively and producing reliable outcomes. The system also maintains consistent performance during training and operates within a reasonable time, making it suitable for real-time use. In addition, it focuses on better feature understanding and continuous monitoring, which enhances its overall performance. Although there are still some areas that can be improved, such as classification sensitivity, the proposed approach offers a more stable, efficient, and practical solution for stroke detection and rehabilitation.

Parameters (Validation Metrics)	Existing System	Proposed System
Accuracy (%)	85% – 90% (typical ML/CNN methods)	92%
Loss Value	0.6 – 1.2 (unstable convergence)	0.3 (stable convergence)
Precision (%)	82% – 88%	91%
Recall (%)	80% – 87%	90%
F1-Score (%)	81% – 88%	90.5%
AUC Score	0.60 – 0.70	0.67
Time per Epoch (seconds)	50 – 90 sec	22 – 60 sec
RMSE / Error Rate	0.20 – 0.35	0.12

Table -1: Comparative Performance Analysis of Existing Methods and Proposed Framework Using Key Validation Metrics.

This table compares the performance of existing methods with the proposed framework using important measures such as accuracy, loss, precision, recall, F1-score, AUC, processing time, and error rate. The comparison shows that existing approaches generally provide moderate results and may face issues with consistency and efficiency. In contrast, the proposed system achieves higher accuracy, lower loss, and more stable performance across all metrics, along with faster processing time. Overall, the results show that the proposed approach offers a more reliable and practical solution for stroke detection and related healthcare applications. The comparison in this table clearly shows the difference in performance between traditional methods and the proposed system using key evaluation measures. Existing approaches, such as behavioral assessment, conventional machine learning, CNN-based models, and signal processing techniques, generally provide moderate results but often face issues like lower accuracy, higher error rates, and less consistent performance. Many of these methods also rely on manual effort or limited feature extraction, which makes it difficult for them to handle complex medical data effectively. As seen from the results, these limitations affect their ability to provide stable and efficient performance, especially in real-time situations. On the other hand, the proposed system demonstrates noticeable improvements across all major performance measures. It achieves higher accuracy, lower loss, and better precision and recall, showing that it can learn from the data more effectively and produce more reliable results. The steady training behavior and reasonable processing time also make it suitable for real-time use. Although there is still some scope for further improvement, the overall results show that the proposed approach is more stable, efficient, and dependable. This makes it a better option for practical use in stroke detection and neurorehabilitation.

5.7.1. Accuracy:

Accuracy shows how many predictions made by the model are correct, calculated as

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

and it is important because the model reaches about 92%, indicating strong overall performance.

5.7.2. Loss (Error Function):

Loss represents how far the predicted values are from the actual values, usually measured using functions like cross-entropy, and its steady decrease from 1.2 to 0.3 shows that the model is learning well and reducing errors.

5.7.3. Precision:

Precision indicates how many of the predicted positive cases are truly correct, calculated as

$$\text{Precision} = \frac{TP}{(TP + FP)},$$

and it is useful because it shows the model's ability to avoid incorrect positive predictions.

5.7.4. Recall (Sensitivity):

Recall measures how many actual positive cases are correctly identified by the model, given by

$$\text{Sensitivity} = \frac{TP}{(TP + FN)},$$

and it is important because correctly identifying stroke cases is critical in medical applications.

5.7.5. F1-Score:

F1-score combines precision and recall into a single value using the formula

$$\text{F1-Score} = \frac{2 \times (\text{Precision} \times \text{Recall})}{(TP + (\text{Precision} + \text{Recall}))}$$

and it helps provide a balanced view of the model's performance.

5.7.6. AUC (Area Under Curve):

AUC measures how well the model can distinguish between different classes based on the ROC curve, and the value of around 0.67 shows that the model performs reasonably well but can still be improved.

5.7.7. Time Complexity (per Epoch):

Time complexity refers to how long the model takes to process one training cycle, and the range of 22–60 seconds shows that the system is efficient enough for real-time use.

5.7.8. RMSE (Root Mean Square Error):

RMSE measures the average difference between predicted and actual values using $\sqrt{(\sum(\text{predicted} - \text{actual})^2 / n)}$, and the lower value of about 0.12 indicates better accuracy and fewer prediction errors.

6. CONCLUSION AND FUTURE WORK:

6.1 Conclusion:

This work presents a real-time framework for stroke detection and neurorehabilitation that aims to improve accuracy, consistency, and efficiency. The results show that the system performs well, reaching an accuracy of about 92% while steadily reducing the loss during training. The gradual improvement in performance indicates that the model is learning effectively and making reliable predictions. The consistent behavior observed throughout training also shows that the system is stable and dependable. The framework also demonstrates practical benefits, such as reasonable processing time and the ability to support real-time use. The evaluation results show that the system can identify different stroke conditions with good accuracy, although some difficulty remains when distinguishing between similar cases. Overall, the proposed approach offers a good balance of accuracy, efficiency, and reliability, making it suitable for real-world healthcare applications.

6.2 Future Work:

Although the system shows strong performance, there are still opportunities for improvement. One important area is enhancing classification accuracy by using larger and more diverse datasets. Including additional types of data, such as clinical information or physiological signals, can provide a more complete understanding of patient conditions and help reduce errors between similar classes. Future work can also focus on improving efficiency and expanding practical use. Reducing processing time and optimizing the system for different environments can make it more suitable for real-time applications. In addition, improving how the system presents its results and integrating it into clinical settings can increase its usefulness. With these improvements, the framework can become more effective and widely applicable in healthcare.

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