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Neuroimage-based Stroke Identification: A Machine Learning Diagnostic Approach

Suhas K C, Yashaswini N, Pavithra M, Sreelakshmi T

Assistant Professor, Department of Computer Science and Engineering, Channabasaveshwara Institute of Technology,
Tumkur, Karnataka, India

U.G Student, Department of Computer Science and Engineering, Channabasaveshwara Institute of Technology,
Tumkur, Karnataka, India

U.G Student, Department of Computer Science and Engineering, Channabasaveshwara Institute of Technology,
Tumkur, Karnataka, India

U.G Student, Department of Computer Science and Engineering, Channabasaveshwara Institute of Technology,
Tumkur, Karnataka, India

ABSTRACT: Stroke and other cerebrovascular diseases rank among the leading causes of death and disability worldwide, but they are largely preventable and treatable. Early stroke detection and quick intervention are critical to lessening the disease's impact and improving patient outcomes. Recently, machine learning has emerged as a promising tool for stroke detection. This study aims to pinpoint effective algorithms, methods, and features to assist medical professionals in making informed decisions for stroke prevention and treatment. We developed an early detection system utilizing brain CT images, combining a genetic algorithm with a bidirectional long short-term memory (BiLSTM) model for detecting strokes in their earliest stages. The system applies a genetic approach within neural networks to select the most relevant features, which are then processed by the BiLSTM model. The system's performance was evaluated through cross-validation, using metrics such as accuracy, precision, recall, F1 score, ROC (Receiver Operating Characteristic), and AUC (Area Under the Curve), and achieved an accuracy rate of 96.5%. We also compared this model with other approaches, including Logistic Regression, Decision Trees, Random Forests, Naive Bayes, and Support Vector Machines, underscoring its potential to support physicians in making accurate, timely decisions about stroke diagnosis and care.

KEYWORDS: Stroke, feature selection, genetic algorithm, LSTM, BiLSTM, CT images.

I. INTRODUCTION

A stroke happens when the brain's blood supply is cut off or a blood vessel within the brain ruptures, leading to severe health impacts worldwide. It is a top cause of death and often results in serious disabilities for survivors. Rapid detection and timely treatment can significantly reduce stroke severity and improve recovery outcomes. Strokes are mainly categorized into ischemic strokes, which result from blocked blood vessels caused by clots or cholesterol deposits, and hemorrhagic strokes, which involve bleeding from a ruptured blood vessel that harms brain cells and disrupts brain functions. This research leverages machine learning to create a structured system for detecting strokes, with the goal of providing deeper insights into stroke causes and building effective models to support healthcare professionals in preventive and treatment strategies. By examining a variety of data sources, such as medical records, genetic profiles, and lifestyle information, the study develops predictive models designed to identify people at high risk of stroke. Through feature selection techniques, it extracts key data points to enhance detection precision and aid in clinical decisions. The research also evaluates how effective, adaptable, understandable, and scalable these algorithms are by testing them against traditional clinical methods on real-world datasets. In the long term, this study aims to utilize machine learning for improved stroke prediction accuracy, thereby lowering stroke incidence and benefiting patient health outcomes. Key contributions of this work include the development of an image-based diagnostic system for stroke detection, the application of genetically optimized CNN to draw essential features from CT images, the comparison of various neural network models, the evaluation of the GA_BiLSTM model's performance relative to other techniques, and the provision of an early detection tool that aids healthcare providers in stroke prevention and treatment. The findings from this study

hold the potential to advance stroke prevention efforts and improve clinical outcomes for affected individuals.

II. LITERATURE SURVEY

In recent years, machine learning algorithms have become increasingly important in predicting stroke risk, particularly in hypertensive patients, by analyzing electronic medical record data. Techniques like Extreme Gradient Boosting (XGBoost) have proven effective in enhancing stroke risk predictions, demonstrating strong capabilities in identifying high-risk individuals. Additionally, ensemble models that integrate various machine learning methods have shown promise in improving the accuracy of these predictions, highlighting the potential of machine learning in stroke risk assessment. The use of deep learning in medical imaging has also revolutionized skull stripping techniques, which are essential for brain image analysis. These methods can be broadly categorized into traditional approaches and deep learning-based methods, especially convolutional neural networks (CNNs). These advancements offer significant improvements in the accuracy and efficiency of stroke detection within clinical settings. Furthermore, deep reinforcement learning (DRL) has shown promise in discovering hidden patterns in evolving datasets. For example, the time-based link prediction model TDRL has outperformed traditional machine learning methods, achieving higher accuracy in dynamic datasets like criminal data. Machine learning applications in clinical stroke detection have expanded with the use of CT and MRI imaging. One study using a CNN hybrid structure achieved 74% accuracy in predicting stroke outcomes, while another combined wavelet entropy-based spider network graphs with a probabilistic neural network, achieving 100% classification accuracy for MRI brain images. These studies highlight the growing effectiveness and reliability of machine learning in stroke detection. Additionally, the integration of statistical methods, such as principal component analysis, has helped improve stroke prediction, especially for patients with high-risk factors like hypertension and advanced age. Despite the progress made, challenges such as high computational complexity and the need for improved prediction accuracy remain. Many current models are computationally expensive and could benefit from optimization. To address these issues, a new diagnostic system integrating a genetic algorithm with bidirectional long short-term memory (BiLSTM) networks has been proposed. This system aims to reduce computational costs while improving prediction accuracy, providing a more efficient and effective approach to stroke prediction using CT scan images.

III. METHODOLOGY

This section outlines the methodology and framework used in this study. The proposed framework, shown in Figure 1, describes the architecture of the stroke diagnosis system. A benchmark dataset is divided into training (70%) and validation (30%) sets using holdout cross-validation. This study uses five CNN architectures—AlexNet, NASNet-Large, VGG-19, Inception V3, and ShuffleNet—to extract robust features from RGB images. The CNNs generate feature vectors with 1000 features, which are then ranked and optimized using genetic algorithms to remove non-optimal features. The algorithm automatically generates mask image without user interaction that contains only text regions to be inpainted.

CNN ARCHITECTURE

CNNs are widely used in deep learning for image recognition, and various models have been employed for medical tasks like diabetic retinopathy classification. Figure 1 illustrates how these models, combined with genetic algorithms, select features systematically.

1. AlexNet

AlexNet, introduced in 2012, consists of 650,000 neurons and 60 million parameters. It uses layers like fully connected, softmax, and convolutional filters with ReLU activation. By adjusting the filters and layers, AlexNet's performance can be optimized. The architecture involves input processing, weighted transformations, activations, and neuron outputs.

2. Inception V3

Inception V3, developed by Google in 2014 and improved in 2015, is a CNN architecture that optimizes local sparsity by using complex modules. It enhances performance in tasks such as object identification, action recognition, and video segmentation. The architecture reduces grid size, extends network filtering activation scale, and uses auxiliary classifiers to improve accuracy.

3. VGG 19

VGG 19, part of the Visual Geometry Group (VGG) networks, is widely used in medical imaging and commercial

applications. Its simple structure, with convolutional layers and max-pooling stages, helps reduce dataset volume.

4. NASNet-Large

NASNet-Large, developed by Google, is an artificial neural network that optimizes feature combinations for large datasets like ImageNet. It achieves impressive results by finding the optimal architecture through a search process.

5. ShuffleNet

Designed for mobile devices in 2017, ShuffleNet speeds up computations by using convolutional methods and shuffled paths to reduce network size while improving accuracy. The architecture was developed by Megvii Inc. for efficient processing on mobile platforms.

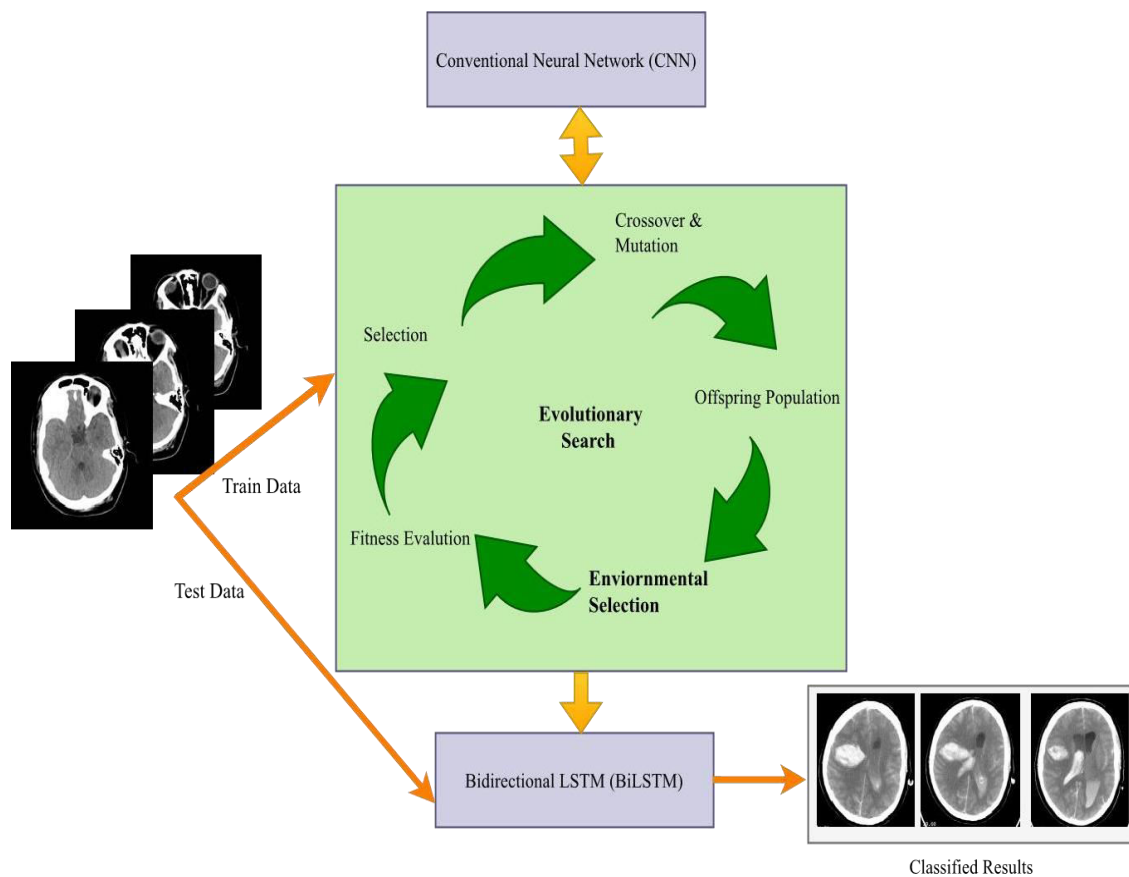


Fig 1: Framework of the proposed model.

IV. RESULTS

This section presents the datasets used in the study and the experimental evaluations that demonstrate the effectiveness of the proposed model. Various validation techniques are commonly employed for the statistical evaluation of machine learning models, including holdout, k-fold cross-validation, and leave-one-out (LOO) cross-validation. However, holdout validation can be problematic for small datasets, as it may not represent the dataset's distribution accurately, leading to biased results. Therefore, when limited data is available, cross-validation is considered the most practical and reliable validation method. This approach helps prevent overfitting and provides a more accurate estimate of model performance. Consistent with previous research, we utilized a ten-fold cross-validation scheme and evaluated the classification results of the proposed model using metrics such as accuracy, precision, recall, and F1-score. These evaluation metrics help assess the model's effectiveness and ensure reliable performance.

DATASET DETAILS

The dataset used in this study was sourced from Kaggle [39] and aimed to identify stroke risk factors such as age, gender, smoking, diabetes, and high blood pressure. It comprised 100 stroke patients aged 16 and older, with 68% of the patients being men and 32% women. Each patient had CT brain images classified as either normal or stroke, including 1551 normal images and 950 stroke images. The normal images were taken from the same patients prior to the occurrence of the stroke. These grayscale images had an initial resolution of 650×650 pixels. To prevent overfitting during training, the dataset was randomly balanced, resulting in a new dataset with 950 normal and 950 stroke images, each resized to 227×227 pixels.

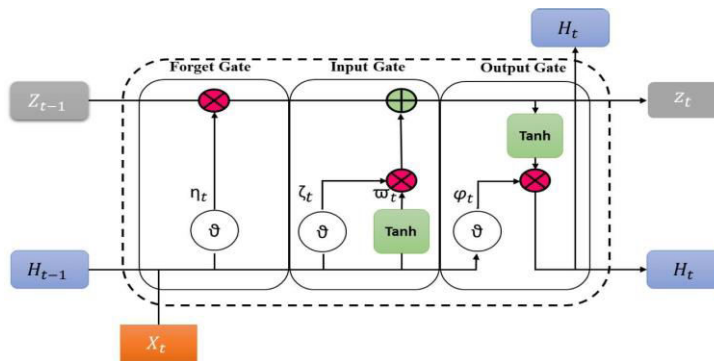


Fig 2: LSTM Memory Cell

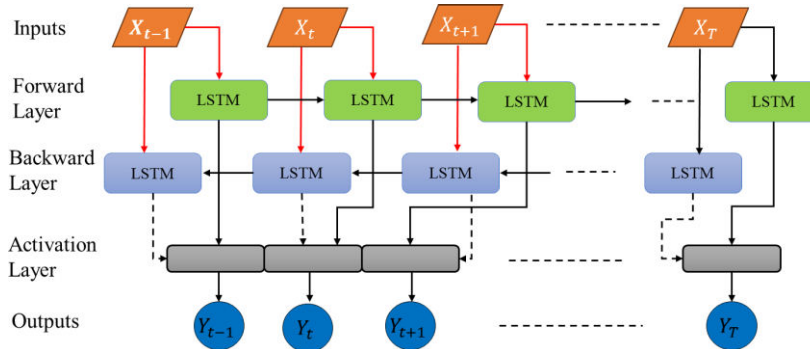


Fig 3: BiLSTM Architecture

EVALUATION METRIC

In this study, accuracy, precision, recall, and F1-score were used as evaluation metrics [40], [41], [42], [43], with the results reported for each classifier. The definitions of the evaluation metrics are as follows:

- Accuracy = No. Correct Prediction/ Total Samples
- Precision = $TP / (TP + FP)$
- Recall = $TP / (TP + FN)$
- $F1_score = 2TP / (2TP + FP + FN)$

where TP represents true positives, FP denotes false positives, TN refers to true negatives, and FN indicates false negatives. The study was conducted on a system running Windows 10 with 32 GB of RAM and an Intel Core i7-8250U CPU at 2 GHz. Python version 3.7.0 was used, and the software package was executed within the Anaconda Spyder IDE.

V. EXPERIMENTAL RESULTS AND DISCUSSION

This section presents the results and compares the proposed model with baseline models. The performance of the proposed model was evaluated against various ML classifiers and DL methods. The results, shown in Tables 1 and 2, reveal that the Support Vector Machine (SVM) outperforms other ML classifiers with 91.45% accuracy, while Naive Bayes performs the worst at 66.21%. Among DL classifiers, the Deep Neural Network (DNN) achieves the highest

accuracy of 95.78%, followed by the Recurrent Neural Network (RNN) at 93.66%. To address issues of data imbalance and small sample sizes, experiments were conducted using features extracted by a Neural Network-based Genetic Algorithm (NN-GA) and fed into Long Short-Term Memory (LSTM) and Bidirectional LSTM (BiLSTM) for stroke detection. The GA_LSTM model achieved a 95% area under the curve (AUC) in the ROC curve. Further experiments with BiLSTM (GA_BiLSTM) resulted in the highest AUC, as shown in Figure 10. The performance of GA_BiLSTM, evaluated using accuracy, precision, recall, and F1-score, shows superior results compared GA_LSTM and other DL/ML models.

ML models	Accuracy	Precision	Recall	F1-score	DL models	Accuracy	Precision	Recall	F1-score
Logistic Regression	75.62	68.56	78.40	75.00	ANN	92.50	88.56	91.40	92.00
Decision Tree	85.00	80.65	88.34	85.00	DNN	95.78	95.26	88.62	95.00
Random Forest	89.53	91.50	86.73	90.00	RNN	93.66	91.50	89.00	94.00
Naive Bayes	66.21	70.00	62.15	61.00					
Support Vector Machine	91.45	89.88	92.00	91.00					

Fig 4: Table 1- Performance of ML classifiers and Table 2- Performance of DL classifiers

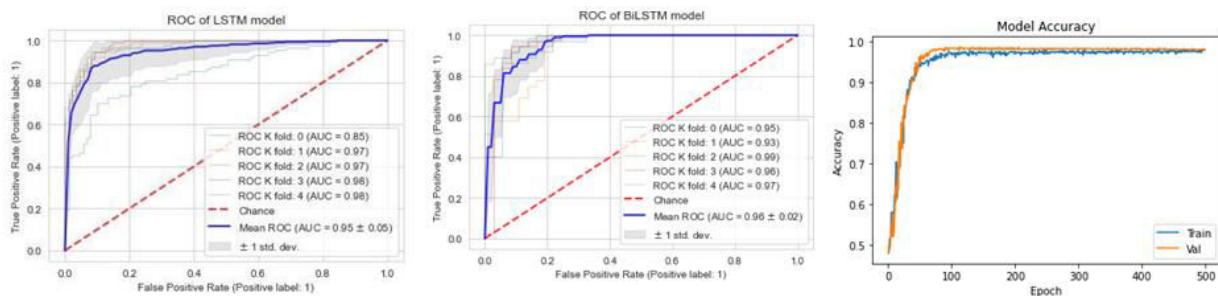


Fig 5: ROC of GA_LSTM., ROC of GA_BiLSTM., Demonstration of validation accuracy of GA_BiLSTM.

COMPARISON WITH PREVIOUS STROKE PREDICTION METHODS

This section examines the performance of the newly proposed stroke detection method and compares it with various machine learning-based approaches introduced by other researchers in recent years. The classification accuracy of the proposed GA_BiLSTM method is compared to other models that have utilized the same Kaggle dataset of brain CT images for stroke prediction which presents the accuracy comparison between the proposed method and other previously proposed techniques. Notably, the new method demonstrates a significant improvement in accuracy over previous studies that have applied machine learning and deep learning techniques for stroke prediction.

VI. CONCLUSION

This study presents a stroke detection method utilizing machine learning techniques, with validation based on an image-based dataset. The proposed model integrates a genetic algorithm and BiLSTM for stroke prediction. A neural network-based genetic algorithm identifies key features from CT brain images, which are then fed into LSTM and BiLSTM models. Various K-fold evaluations were conducted to identify the most effective classification method, and different machine learning algorithms were tested for stroke prediction. The experimental results demonstrate that the proposed model outperforms other models in terms of efficiency. To enhance stroke detection in future studies, we plan to explore more complex models capable of automatic stroke prediction. While this research used deep learning models on a relatively small dataset, larger datasets typically yield better performance. Thus, increasing the sample size in future work will likely improve the model's accuracy. Additionally, data quality is crucial for the performance of deep learning models, so future efforts will focus on improving data quality through new methods. Furthermore, to gain the trust of healthcare professionals, it is essential to incorporate explainable AI techniques that can clarify the model's decision-making process. Moving forward, we aim to develop such explainable AI methods to empower healthcare professionals in making more informed decisions based on AI-driven results.

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