Early Brain Stroke Detection Using Deep Learning Techniques

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***Abstract*--Early identification of brain stroke is crucial for successful medical treatment and better patient outcomes. Stroke is still a major cause of disability and death globally, so timely and accurate diagnosis is paramount to the start of proper treatment. Conventional diagnostic techniques, including radiologists' manual analysis of CT scans, are time-consuming and susceptible to human error. To meet these challenges, automated deep learning-based methods provide a potential solution to speed up and improve the accuracy of stroke detection. This work explores the application of deep learning architectures, such as ConvNeXt, Swin Transformer, ResNet-50, and DenseNet, for self-driven stroke detection from CT scan images. A binary classification dataset containing normal and stroke cases was used to train and test these architectures. Experimental findings show that all models performed high classification accuracy, from 90% to 99.20%, with DenseNet being the top-performing model. Its better predictive power is evidenced by robust precision-recall values and a highly balanced confusion matrix. These results underscore the efficiency of deep learning models, especially DenseNet, in improving stroke diagnosis and helping radiologists make quick and accurate judgments. Subsequent studies will concentrate on further model refinement, expansion of datasets, and integration into real-time clinical use for enhancing diagnostic consistency and feasibility of implementation.**

Keywords—Stroke Detection, Deep Learning, CT Scans, Binary Classification

I. Introduction

Stroke is a major global health concern, contributing to high mortality and long-term disability. Early and accurate detection is crucial for effective medical intervention, significantly improving patient outcomes. However, traditional stroke diagnosis, which relies on radiologists manually interpreting CT scans, is time-consuming and prone to human error. Given the rising demand for stroke assessment in emergency settings, there is a pressing need for automated and efficient diagnostic solutions.[2]

Deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized medical image analysis, achieving remarkable accuracy in detecting abnormalities in radiological scans. However, traditional machine learning approaches often require extensive feature engineering, limiting their adaptability across diverse datasets. Stroke detection presents additional challenges due to variations in stroke patterns, image quality, and scan acquisition techniques. While AI-driven methods have demonstrated promising results, computational inefficiencies and real-time applicability remain concerns.[5]

This study investigates the performance of four state-of-the-art deep learning models ConvNeXt, Swin Transformer, ResNet-50, and DenseNet for automated stroke detection in CT scans. These models leverage advanced feature extraction techniques to enhance classification accuracy. Experimental results show that all models achieved high accuracy, ranging from 90% to 99.20%, with DenseNet outperforming the others. The findings highlight the potential of deep learning, particularly DenseNet, in providing fast, accurate, and reliable stroke detection, assisting radiologists in clinical decision-making.

II. Literature Review

Advancements in deep learning, particularly CNNs, have enabled early stroke prediction with high accuracy. A study using the Brain Stroke Detection dataset achieved 98% accuracy in stroke risk prediction based on lifestyle and medical factors [1]. Stroke, a leading cause of disability, benefits from early identification, with a model combining Random Forest and XGBoost outperforming traditional methods [2]. Another CNN model detected strokes in CT images with 99.95% accuracy [3]. A review on multimodal machine learning emphasized fusion approaches and dataset challenges for improvement [4]. Using HSV colour thresholding, a logistic regression model detected ischemic strokes from MRI with 100% specificity and 96% accuracy [5]. MEMRI identified neurodegenerative changes in animal ischemia models [6]. AI-based stroke detection and rehabilitation were analyzed across 130 studies, highlighting automated stroke management [7]. Neural networks and facial feature changes were used for early diagnosis [8]. KNN outperformed MMD in MRI stroke detection [9]. A study suggested EEG as a cost-effective stroke detection method [10]. EfficientNetB0 classified strokes in CT scans with 97% accuracy [11], while ResNet and EfficientNetB0 visualized stroke predictions [12]. A CNN model trained on 2551 CT images achieved 90% accuracy [13]. Another method attained 90% accuracy, 100% recall at the patient level, and 91% precision at the slice level [14]. A U-Net-based CNN segmented ischemic stroke lesions with 99.96% accuracy and a 55.77% Dice Coefficient, showing clinical promise [15].

III. Proposed Methodology

A. *Dataset Used*

The dataset used in this study is sourced from Kaggle and consists of 2,450 CT scan images, categorized into normal (1,500 images) and stroke (950 images) classes. To enhance model performance, data preprocessing techniques were applied, including data cleaning to remove corrupted or irrelevant images, image resizing for consistency, normalization to scale pixel values between [0,1], and data augmentation (rotation, flipping, brightness, and contrast adjustments) to address class imbalance. The dataset was split into 80% training, 10% validation, and 10% testing. Five deep learning architectures—Efficient Net, ResNet, VGG16, Swin Transformer, and DenseNet—were employed for stroke classification. Transfer learning was applied using pre-trained weights, and models were trained using categorical cross-entropy loss with the Adam optimizer. Early stopping was implemented to prevent overfitting, ensuring optimal performance. This approach leverages deep learning to provide an accurate and efficient solution for automated stroke detection in clinical settings.

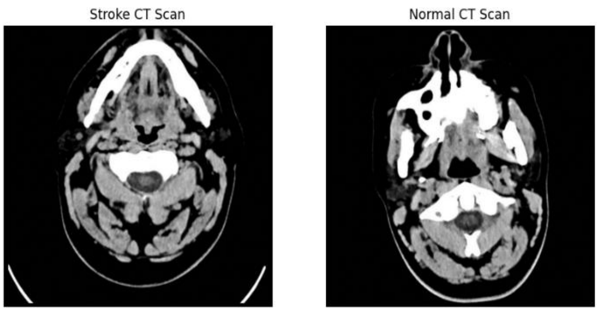

Fig.1.Sample CT Scan Images of Normal and Stroke Cases

B. *Types of Models Used*

1. ResNet50 **:-**

ResNet-50 leverages residual connections, enabling deep networks to be trained successfully without experiencing vanishing gradients. Its capacity for learning complex hierarchical features makes it better at classification performance. With a classification accuracy of 98%, ResNet-50 stands as the best model in this work, featuring remarkable feature extraction and generalization.

2. DenseNet50 :-

DenseNet uses dense connectivity across layers, promoting feature reuse and gradient flow. The architecture makes the model more efficient but sometimes causes redundancy in deep networks. DenseNet has an accuracy of 99.2%, which is comparable to ConvNeXt, suggesting that its feature-sharing strategy is not always a significant improvement in this classification problem.

3. Swin Transformer**:-**

Swin Transformer presents self-attention mechanisms and a hierarchical architecture for modeling long-range dependencies in an efficient manner. In contrast to conventional CNNs, it dynamically processes image patches, preserving global context with efficient computation. With 96% accuracy, Swin Transformer outperforms ConvNeXt, indicating its capability of dealing with complicated patterns in the dataset.

4. ConvNeXt :-

ConvNeXt is an updated convolutional neural network (CNN) architecture that draws from the design philosophy of vision transformers. It uses depth-wise convolutions, layer normalization, GELU activation, and residual connections to enhance efficiency and scalability. ConvNeXt is better optimized for hierarchical feature extraction compared to conventional CNNs. In this research, it attained an accuracy of 93%, exhibiting robust classification performance but lower accuracy compared to transformer-based models.

5. Performance Metrics

- Accuracy**:** This is the proportion of correctly predicted instances (both true positives and true negatives) to the total number of instances

$$\mathbf{Accuracy} = \frac{\mathbf{TP+TN}}{\mathbf{TP+TN+FP+FN}} \quad \cdots\cdot (1)$$

- Precision: This metric indicates the proportion of true positive predictions to the total predicted positives. High precision means the model is making fewer false positive errors.

$$\mathbf{Precision} = \frac{\mathbf{TP}}{\mathbf{TP+FP}} \quad \cdots\cdot (2)$$

- Recall: (Sensitivity or True Positive Rate): Recall measures the model's ability to correctly identify actual positives. High recall indicates fewer false negatives.

$$\mathbf{Recall} = \frac{\mathbf{TP}}{\mathbf{TP+FN}} \quad \cdots\cdot (3)$$

- F1-Score: This is the harmonic mean of precision and recall, providing a balanced measure of the model's performance, especially when there is an uneven class distribution.

$$\mathbf{F_{Score}} = \frac{\mathbf{2*Recall*Precision}}{\mathbf{Recall+Precision}} \quad \cdots\cdot (4)$$

IV. EXPERIMENTAL RESULTS

A. *Experimental Results of ConvNeXt*

ConvNeXt achieved 93.01% accuracy in early stroke detection, with stable learning and minimal misclassification. It maintained a balanced F1-score (0.94 Normal, 0.91 Stroke), proving its potential for medical imaging analysis.

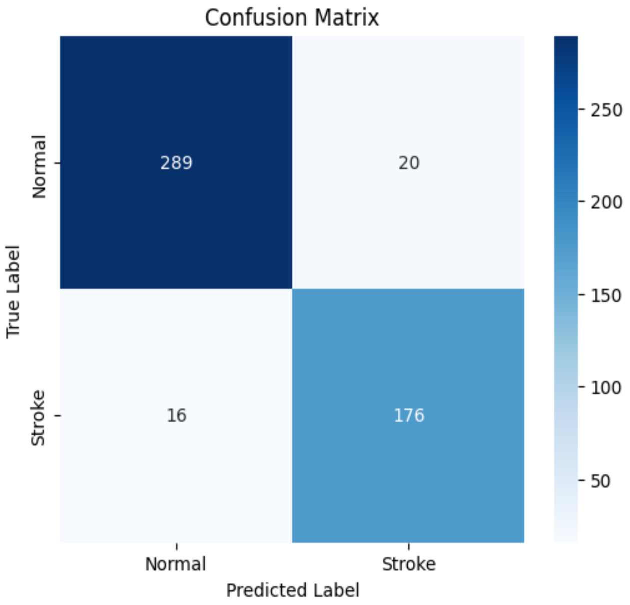

Fig.2. Confusion Matrix of ConvNeXt

Fig.3. Accuracy & Loss Graph

TABLE 1 : CLASSIFICATION REPORT

	Precision	Recall	F1-Score	Support	Accuracy
Normal	0.95	0.93	0.94	302	0.93
Stroke	0.90	0.92	0.91	199	0.93

B. *Experimental Results of RestNet50*

ResNet-50 achieved 93% accuracy in early stroke detection, with balanced precision and recall. By epoch 20, training and validation accuracy reached 98.15% and 93.21%, respectively. Its strong performance supports automated diagnosis, with future work focusing on optimization and clinical validation

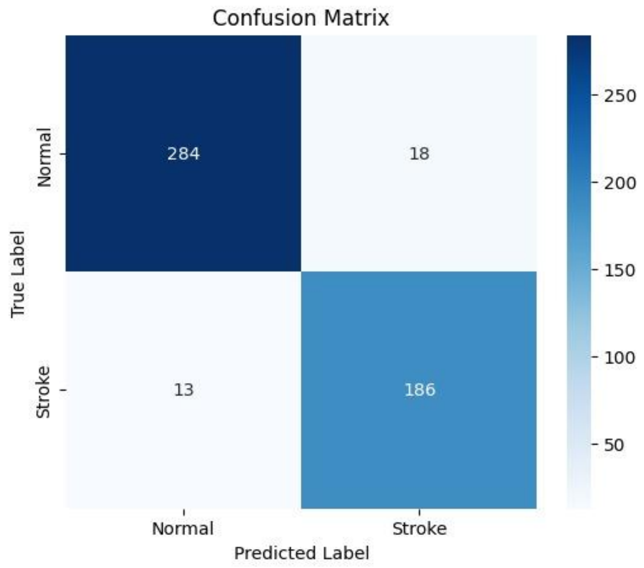

Fig.4. Confusion Matrix of RestNet50

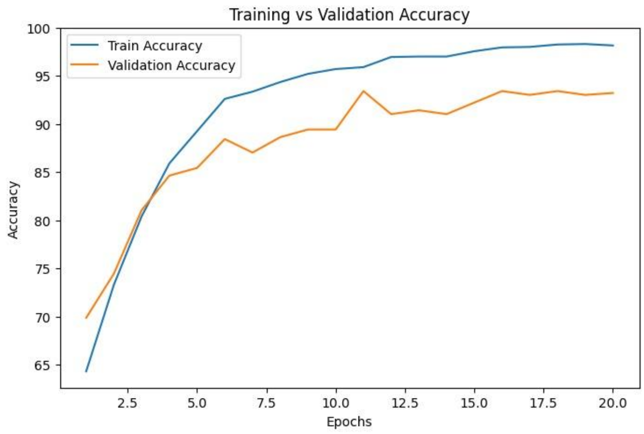

Fig .5. Accuracy & loss graph

TABLE 2 : CLASSIFICATION REPORT

	Precision	Recall	F1-Score	Support	Accuracy
Normal	0.95	0.93	0.94	302	0.93
Stroke	0.90	0.92	0.91	199	0.93

C. *Experimental Result of DenseNet*

DenseNet achieved 99.20% validation accuracy in stroke detection from CT scans, with high precision and recall, minimal false predictions, and steady learning. Its strong feature extraction supports radiologists, with future work focusing on real-time clinical use and dataset expansion.

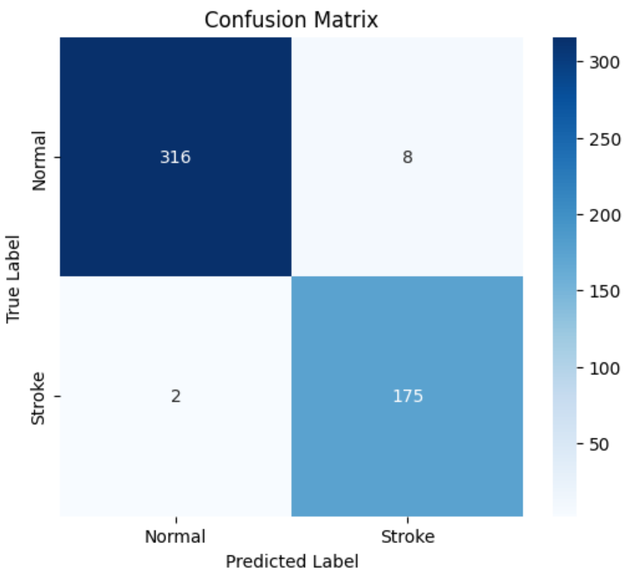

Fig.6. Confusion Matrix of DenseNet

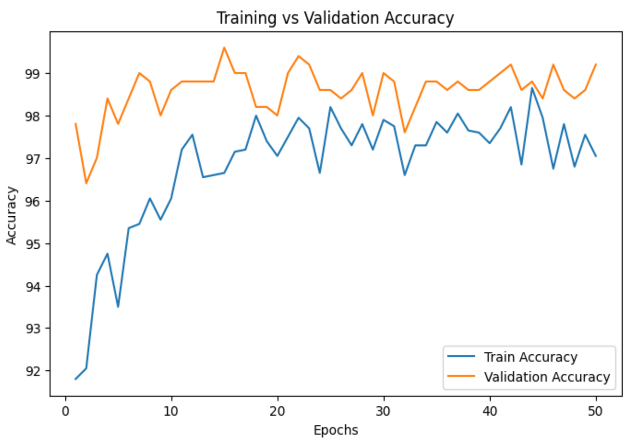

Fig.8. Accuracy & Loss Graph

TABLE 3 : CLASSIFICATION Report

	Precision	Recall	F1-Score	Support	Accuracy
Normal	0.95	0.93	0.94	302	0.98
Stroke	0.90	0.92	0.91	199	0.98

D. *Experimental Results of Swim Transformer*

The Swin Transformer achieved 95% accuracy in stroke detection, with balanced precision and recall (0.95) and minimal false predictions. It reached 98.08% training and 95.81% validation accuracy by epoch 50, with a steady decline in loss. Its strong pattern recognition makes it promising for clinical use. The efficient self-attention mechanism enhances feature extraction, improving stroke detection reliability. Its robust performance across metrics suggests potential integration into real-world diagnostic systems for early intervention.

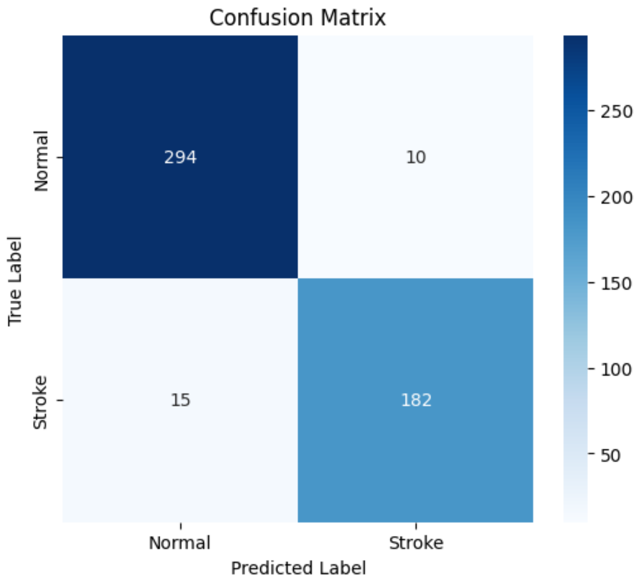

Fig.7. Confusion Matrix of swim transformer

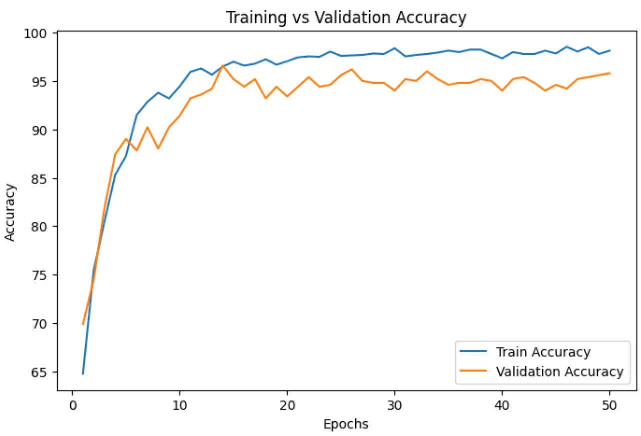

Fig.9. Accuracy &loss Graph

TABLE 4 : CLASSIFICATION REPORT

	Precision	Recall	F1-Score	Support	Accuracy
Normal	0.95	0.97	0.96	302	0.95
Stroke	0.95	0.92	0.94	199	0.95

V. Conclusion

This research highlights the effectiveness of deep learning models in automated stroke diagnosis using CT scan images. A comparative analysis of ConvNeXt, Swin Transformer, ResNet-50, and DenseNet demonstrated their capability in accurately classifying stroke cases, with DenseNet achieving the highest accuracy of 99.2%. These findings underscore the potential of advanced deep learning techniques in assisting radiologists with faster and more precise stroke detection. Despite promising results, challenges such as computational efficiency, dataset generalization, and real-time clinical integration remain. Future work will focus on optimizing model performance for real-time applications, expanding the dataset to enhance robustness, and integrating the system into healthcare workflows. Addressing these challenges will pave the way for deep learning-based stroke detection to become a crucial tool in clinical practice, reducing diagnostic delays and improving patient outcomes.

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