Optimizing Ischemic Stroke Diagnosis: Enhanced Performance with MobileNetV2 in Automated Image Segmentation

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Abstract: Early identification of ischemic stroke leads to a speedy recovery from severe repercussions and irreversible brain damage. Stroke affects people differently, with varying experiences during the event and variable paths to recovery afterward. Radiologists utilize CT (Computed Tomography) scans to diagnose stroke patients, but occasionally they struggle to spot abnormalities in the pictures. Computer-aided diagnosis, (CAD), is a crucial component of medical image analysis that enables radiologists to quickly assess and interpret abnormalities. Using CNN deep learning techniques, our research aims to establish an automated approach for diagnosing ischemic strokes in their early stages. Based on CNN models such as VGG16, VGG19, ResNet50 and MobileNetV2, our suggested methodology divides brain stroke CT (Computerized Tomography) images into ischemic and non-ischemic images.

Keywords: Deep Learning, VGG16, VGG19, ResNet50, MobileNetV2, Ischemic Stroke, Computed Tomography (CT)

1 Introduction

Brain strokes, also known as cerebrovascular accidents [1] (CVAs), can be broadly categorized into two main types: ischemic strokes and hemorrhagic strokes. Ischemic strokes, constituting approximately 87% of all strokes, arise due to blood clotting or blockage forms in a blood vessel supplying the brain. Thrombotic strokes involve the formation of a clot (thrombus) within a brain blood vessel, while embolic strokes result from a clot originating elsewhere in the body, often the heart, and traveling to the brain. On the other hand, hemorrhagic strokes [2] though less common, are more severe, characterized by bleeding within or around the brain. Intracerebral hemorrhage (ICH) involves bleeding directly into the brain tissue, typically from the rupture of small arteries, while subarachnoid hemorrhage (SAH) entails bleeding in the space between the brain and its covering tissues, often caused by an aneurysm rupture. Recognizing the specific type of stroke is crucial for determining appropriate treatment strategies, as ischemic strokes [3] may require interventions to restore blood flow, while hemorrhagic strokes necessitate measures to control bleeding and manage intracranial pressure.

Understanding the diverse causes and risk factors associated with strokes, such as hypertension, diabetes, smoking, and age, underscores the importance of prompt recognition of stroke symptoms and seeking immediate medical attention to minimize potential long-term consequences and enhance recovery prospects [4-5]. Patients often experience a sudden onset of Prominent symptoms may include numbness or paralysis on one side of the body, difficulties speaking or comprehending, and vision abnormalities. Additionally, the emotional and psychological toll on both patients and their families underscores the multifaceted

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challenges associated with ischemic strokes [6]. The diagnosis must, however, rely on medical professionals to evaluate the CT scan because the location of the ischemic stroke is not readily apparent.

Deep learning [7] plays a pivotal role in addressing challenges associated with the classification and diagnosis of different types of brain strokes. In the context of ischemic strokes, deep learning models, such as CNNs, can be trained on large datasets of brain CT or MRI scans to automatically identify patterns associated with the presence of ischemia. The ability of these models to learn intricate features from imaging data enables them to detect subtle abnormalities indicative of ischemic strokes, which may not be easily discernible to the human eye. The goal of our research a promise to help establish an effective and an effective and dependable tool for the early diagnosis of ischemic strokes by integrating the CNN models VGG16, VGG19, ResNet50, and MobileNetV2. This study aims to improve patient outcomes by enabling timely medical interventions. The reliable identification of ischemic stroke may arise from the fusion of the four models.

2 Related Work

With the rapid development of deep learning, computer vision techniques have been split into two categories: deep learning approaches and classical methods. This section explains relevant research on brain stroke and the advantages of deep learning over traditional techniques.

Nishio et al. [8] and other researchers introduced a novel approach for the automatic detection of acute ischemic stroke (AIS) utilizing non-contrast computed tomography (CT) images. The paper presented a two-stage deep learning model integrating YOLO3 and VGG16, which was trained on 238 sets of head CT images annotated with AIS-related results. The model achieved 37.3% sensitivity, while the radiologist had 33.3% without software aid and 41.3% with software aid, with false positives of 1.265, 0.327, and 0.388, respectively.

Sahoo et al. [9] and contributed to the field with a paper addressing the automatic identification of early ischemic lesions on non-contrast CT scans through a deep learning approach. Their research introduces an innovative method for detecting these lesions in acute stroke cases, revealing that a customized Convolutional Neural Network (CNN) model. This custom CNN achieved a noteworthy sensitivity of 86.95% in identifying ischemic non-contrast CT slices. Chin et al. [10] and fellow researchers, a groundbreaking paper was presented on the automated early detection of ischemic stroke through the utilization of a deep learning algorithm. The study employed a dataset comprising 256 patch images to train and test the CNN module, showcasing its efficacy in achieving a remarkable accuracy exceeding 90% in the recognition of ischemic stroke.

G.R. Krishna et al. [11] Addressing the challenging task of recognizing and defining brain cancers through Magnetic Resonance Imaging (MRI), this paper introduces a solution that overcomes drawbacks in the existing CNN+DWA (Distance Wise Attention) model by proposing a hybrid model incorporating U-NET and CNN+DWA. While CNN remains a robust choice for brain tumor identification, it exhibits inaccuracies when tumors exceed 1/3rd of the brain volume. This CNN model employs two approaches to capture both local and global characteristics, enhancing brain tumor segmentation accuracy.

Deep learning algorithms have demonstrated exceptional performance in several tasks recently [12-13], particularly in the analysis of medical pictures. CNN are deep learning algorithms that are mostly utilized in radiology and other computer vision tasks. This paper will undertake analysis using the deep learning algorithm and publicly available CT images, based on the findings of the literature review. After pre-processing the image to remove extraneous information, the system will input the processed image into a particular CNN to analyze and detect ischemic strokes early.

The suggested model outperforms Sahoo et al.[9] models (0.75 to 0.80) in terms of accuracy (0.81 to 0.92) and Yeu-Sheng Tyan et al.[14] sensitivity (83%). It also outperforms Shugun Zhang et al.[15] precision (89.77%). In comparison to Dritsas et al.[16] 89.90% accuracy and Nielsen et al.[17] AUC of 0.88 ± 0.12, the suggested model outperforms them in accuracy, sensitivity, precision, and AUC.

3 Methodology

Our research methodology focuses on the early detection of ischemic stroke involving the collection and pre-processing of diverse CT image datasets related to brain strokes. The paper uses CNN models such as VGG16, VGG19, ResNet50, and MobileNetV2 for binary stroke classification and evaluates their performance using accuracy and precision measures on a test set. Ensemble modelling, hyperparameter fine-tuning, and visualization tools all improve model robustness and decision-making knowledge. The final trained ensemble model, which includes these CNN models, is used for real-world stroke detection, with a focus on optimizing features and enhancing class separability, particularly for ischemic strokes. The proposed architecture was depicted in the below Figure 1.

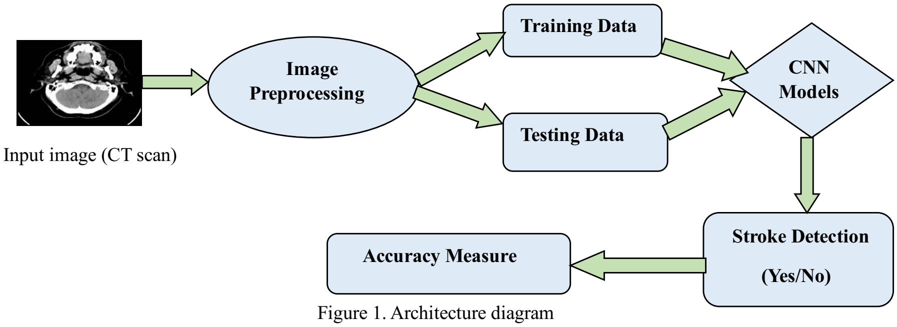


Figure 1. Architecture diagram

In the proposed work, pre-processing was applied on the input image data set to adjust the size of the input as per the model and then scaling is applied for the normalization. Figure 2.a ,b ,c and d indicated the original image and cropped image.

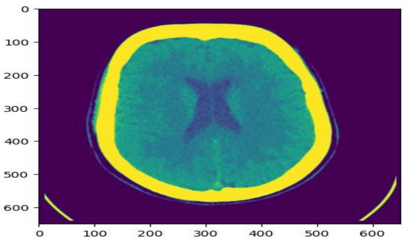


Figure 2.a.Original Image 650X650 size

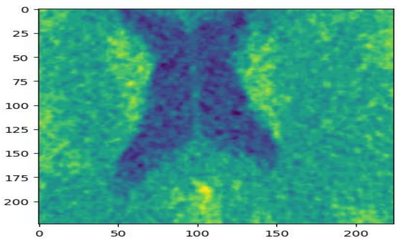


Figure 2.b.Cropped Image 224X224 size

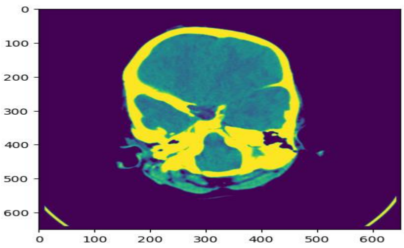


Figure 2.c.Original Image 650X650 size

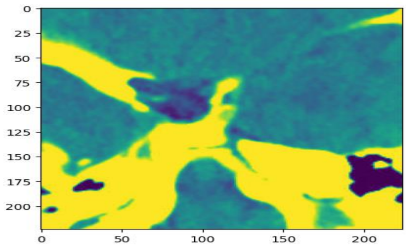


Figure 2.d.Cropped Image 224X224 size

After pre-processing VGG16, VGG19, ResNet50, and MobileNetV2 models were applied on the training data set then and then used test data to evaluate the model performance.

Dataset

The study utilizes a dataset named the Brain Stroke Prediction CT scan image Dataset[18], which consists of 2,536 images specifically curated for the early detection of ischemic strokes. The dataset focuses on binary classification, labelling images as either "Ischemic" if a stroke is present or "Not Ischemic" if it is absent. The dataset is divided into training (1,864 images), testing (437 images), and validation (235 images) sets, denoted as stroke train, stroke test, and stroke validation, respectively. The brain stroke prediction CT scan images in this study are provided in JPG format and have a standardized size of 224×224 pixels. Various augmentation strategies are applied to increase the number of images, contributing to a more comprehensive dataset, and improving the overall performance and resilience of the neural network. Sample images were shown in Figure 3.

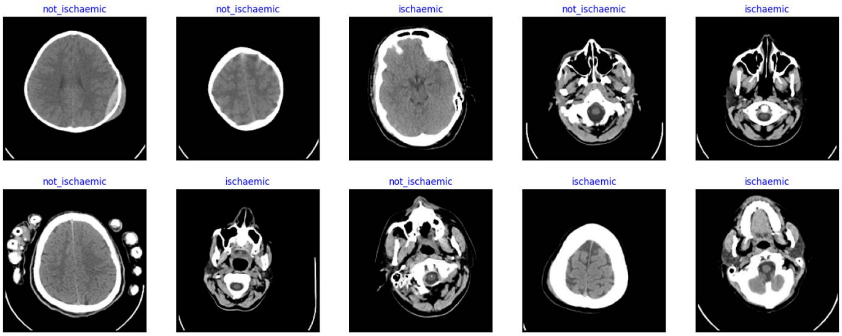


Figure 3. Brain Stroke Prediction CT scan image Dataset

4 Experimental Setup

A new Colab notebook is created to organize and execute code in a cloud-based environment with free GPU and TPU resources. Importing necessary libraries such as PyTorch or TensorFlow is done, and datasets downloaded from Kaggle which are publicly accessible sources and uploaded to Google Drive. Libraries like PIL or OpenCV are used for data preprocessing activities like loading, resizing, normalization, and augmentation. Using Colab's GPU or TPU acceleration, the model architecture is created, assembled, and trained on the dataset for effective training. With the use of programs like Matplotlib, metrics for model evaluation are examined and visuals are produced. Key aspects are documented, model exporting, and hyperparameter adjustment are all part of the experimental setup. Colab is a flexible platform for deep learning research and development because of its collaborative features, which make sharing and version control easier.

Evaluation Parameters

In the performance evaluation phase, important measures like accuracy, precision, recall, and F1 score are used to evaluate how well the models forecast cotton leaf diseases. These measures offer a sophisticated perspective of the models' abilities by weighing sensitivity, accuracy, and the capacity to prevent false positives.

Accuracy:

The percentage of correctly categorized cases among all the predictions is known as accuracy. It offers a broad indicator of how accurate the model's predictions are generally.

$$Accuracy = \frac{True\ Positives + True\ Negatives}{Total\ Instances} \quad (1)$$

Precision:

By showing the percentage of cases that are genuinely positive but are projected as positive, precision calculates the accuracy of positive forecasts. It is particularly helpful in circumstances when false positives can have detrimental consequences.

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

Recall (Sensitivity or True Positive Rate):

Recall evaluates the model's capacity to correctly identify positive cases from the total number of actual positive instances. It is sometimes referred to as sensitivity or true positive rate. It is particularly crucial in circumstances where it is undesirable to overlook positive examples.

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

F1 Score:

The harmonic mean of recall and precision, which offers a ratio of the two measurements.

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

Specificity (True Negative Rate):

The percentage of accurate negative forecasts among all real negative occurrences.

$$Specificity = \frac{TN}{TN+FN} \tag{5}$$

Results

The proposed methodology has been rigorously evaluated and demonstrates its effectiveness in early detection of acute ischemic stroke. The model's performance was gauged using various metrics, which are summarized as follows:

VGG16

The performance of the VGG16 model on the brain stroke prediction CT scan image dataset depicted in the below figure 4,5,6 and table 1. The accuracy rate is 81.69% for both the Ischemic and Non-Ischemic classes. Figure 5 shows the training and validation accuracy as well as the training and validation loss graph. The True Positive - False Positive Rates trade-off is shown by the ROC curve in figure 6, where a higher AUC denotes improved class discrimination in the model. The performance of the VGG16 model, producing a higher AUC of 0.85.

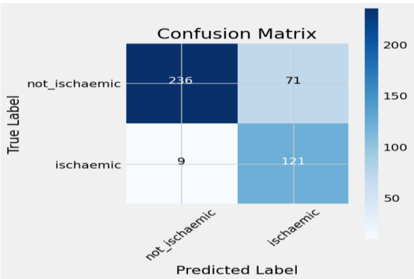


Figure 4. Confusion Matrix

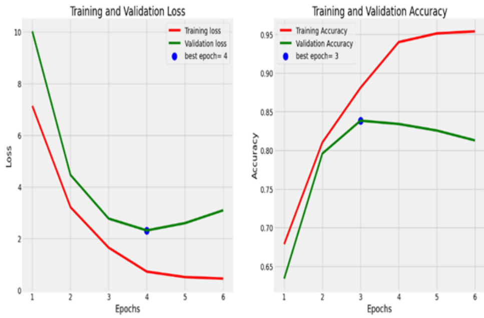


Figure 5. Training and Validation Graph

Table 1.

Metrics	Ischemic	Not Ischemic
Recall	0.93	0.77
Precision	0.63	0.96
F1-Score	0.75	0.86
Accuracy	81.69%	81.69%

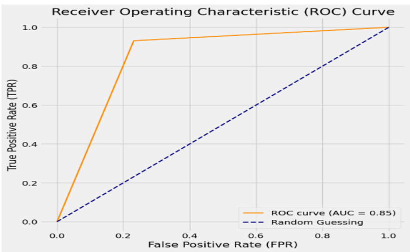


Figure 6. ROC curve

VGG19

The performance of the VGG19 model on the brain stroke prediction CT scan image dataset depicted in the below figure 7,8,9 and table 2. The accuracy rate is 90.16% for both the Ischemic and Non-Ischemic classes. Figure 8 shows the training and validation accuracy as well as the training and validation loss graph. The True Positive - False Positive Rates trade-off is shown by the ROC curve in figure 9, where a higher AUC denotes improved class discrimination in the model. The performance of the VGG19 model, producing a higher AUC of 0.90.

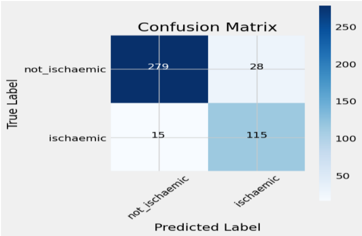


Figure 7. Confusion Matrix

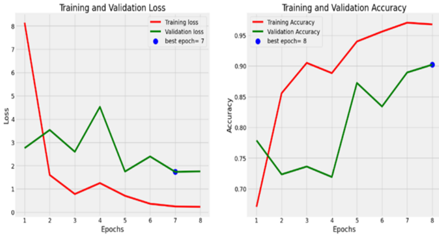


Figure 8. Training and Validation Graph

Table 2.

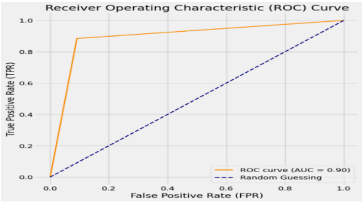


Figure 9. ROC curve

Metrics	Ischemic	Not Ischemic
Recall	0.88	0.91
Precision	0.80	0.95
F1-Score	0.84	0.93
Accuracy	90%	90%

ResNet50

The performance of the ResNet50 model on the brain stroke prediction CT scan image dataset `depicted in the below figure 10,11,12 and table 3. The accuracy rate is 86.04% for both the Ischemic and Non-Ischemic classes. Figure 11 depicts training and validation accuracy as well as the training and validation loss graph. The performance of the ResNet50 model, producing a higher AUC of 0.88.

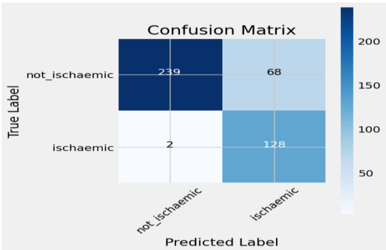


Figure 10. Confusion Matrix

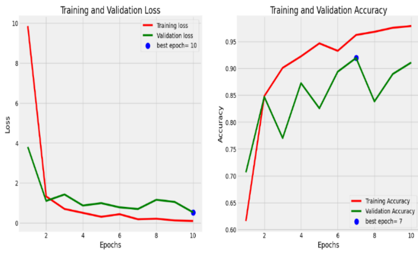
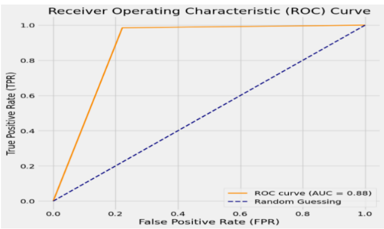


Figure 11. Training and Validation Graph

Table 3.



Metrics	Ischemic	Not Ischemic
Recall	0.82	0.88
Precision	0.74	0.92
F1-Score	0.78	0.90
Accuracy	86.04%	86.04%

Figure 12. ROC curve

MobileNet

The performance of the MobileNetV2 model on the brain stroke prediction CT scan image dataset depicted in the below figure13,14,15 and table 4. The accuracy rate is 92.22% for both the Ischemic and Non-Ischemic classes. Similarly recall, precision and F1-score for the class Ischemic is 92,83,88 and for the class Not Ischemic is 92,97,94 respectively given in Table 8.Figure 14 depicts the training and validation accuracy as well as the training and validation loss graph. The True Positive - False Positive Rates trade-off is shown by the ROC curve in figure 15, where a higher AUC denotes improved class discrimination in the model. The performance of the MobileNetV2 model, producing a higher AUC of 0.92.

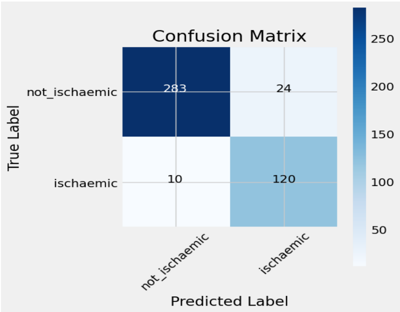


Figure 13. Confusion Matrix

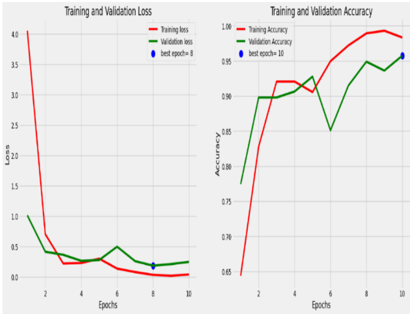


Figure 14. Training and Validation Graph

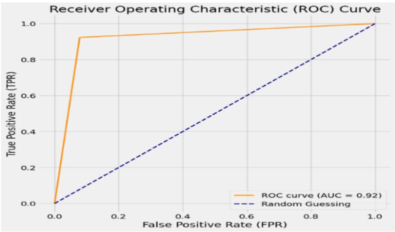


Figure 15. ROC curve

Table 4.

Metrics	Ischemic	Not Ischemic
Recall	0.92	0.92
Precision	0.83	0.97
F1-Score	0.88	0.94
Accuracy	92.22%	92.22%

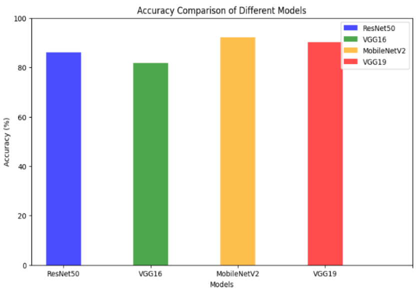


Figure.16 Comparison Graph for accuracy

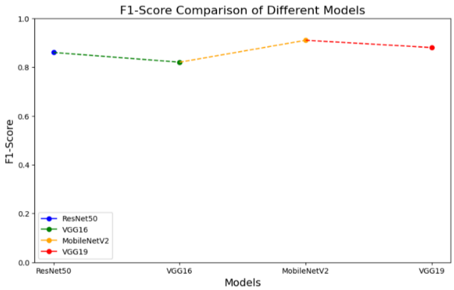


Figure.17 Comparison graph for F1-Score

Neural network models are compared for accuracy as shown in Figure. 16, and MobileNetV2 scores the highest accuracy(92%), followed by VGG19 (90%). With an accuracy of 86%, ResNet50 has good performance, while VGG16 has the lowest accuracy of all the models, at 81%.The F1-Score comparison among neural network models in Figure.17 reveals that MobileNetV2 achieves the greatest F1-Score (0.91).VGG19 closely follows with an F1-Score of 0.90, showcasing a strong balance as well. ResNet50 shows good performance with an F1-Score of 0.86, while VGG16 lags with the lowest F1-Score among the models at 0.82.

5 Conclusion

In conclusion, our research focuses on leveraging Convolutional Neural Network (CNN) models, including ResNet50, VGG16, MobileNetV2, and VGG19, to create an automated approach for diagnosing ischemic strokes in their early stages. The evaluation metrics, including Recall, Precision, F1-Score, and Accuracy, were employed to assess the performance of these models on the task of distinguishing between ischemic and non-ischemic brain stroke CT images. MobileNetV2 exhibited the most recall of 0.91, shows a strong ability to detect true positive cases of ischemic strokes. VGG19 demonstrated the highest precision at 0.89, showcasing its accuracy in predicting positive cases. The F1-Score, which balances precision and recall, was consistently high across all models, with values ranging from 0.86 to 0.88. Additionally, accuracy percentages were notable, ranging from 80.16% to 90.16%. These findings suggest that the proposed CNN-based methodology, utilizing models like MobileNetV2, VGG16, VGG19, and ResNet50, holds promise for early identification of ischemic strokes from CT images. The high recall values indicate a strong capability to detect positive cases, while high precision and F1-Score values emphasize the accuracy of the positive predictions.

Our research underscores the potential of computer-aided diagnosis (CAD) in assisting radiologists with a rapid and accurate interpretation of CT scans, particularly in scenarios where early identification of ischemic strokes is crucial for patient outcomes. The combination of advanced deep learning techniques and medical image analysis offers a viable avenue of increasing the effectiveness and reliability of brain stroke diagnosis, potentially leading to faster recovery and mitigating severe consequences associated with delayed identification. Further validation and refinement of these models in clinical settings are essential steps for transitioning towards practical applications in healthcare.

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