2024 5th International Conference on Innovative Computing (ICIC) | 979-8-3315-1929-2/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICIC63915.2024.11116268

Enhanced and Interpretable Brain Stroke Detection with High Accuracy using ViT B-16 Model

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***Abstract*—Brain stroke is a type of medical emergency that requires prompt and appropriate diagnosis to prevent more brain damage and improve patient outcomes. Standard diagnostic approaches are generally CNN-based but lack interpretability, and still struggle to capture long-range dependencies in medical images, which has limited their application at the clinic. In this study, this challenge was addressed by using the B-16 ViT model for automated stroke detection in the brain. On the other hand, rare details of the subtle spatial relationships are captured very well in scans of the brain and later become useful in looking for faint abnormalities in the spread of strokes across regions. For more confident predictions, CAMs [1] are used, thereby visually explaining to the reader which regions of the image influence model decisions on classification. It was found that rigorous evaluation reported over 96% accuracy along with high precision, recall, and F1-score compared with the state-of-the-art CNN-based models. Besides this, transparency is another aspect for which this model is closer to clinical applications, using CAMs. The architecture of this very strong performing and, at the same time, interpretable ViT B-16 model is extremely promising to promote advancement in stroke diagnosis and better patient care in real-world settings.**

***Keywords*—Brain Stroke Detection, CAM, Vision Transformer, Medical Image Analysis, Heatmap Visualization.**

I. Introduction

Brain stroke is very dangerous, especially among people over the age of 65. It is caused by either blockage or rupture of blood vessels in the brain that quickly leads to the deprivation of oxygen and nutrition for brain tissues. If treatment is not received in time, then this could lead to death, disability, or damage to the brain. Worldwide, it ranks as the fifth cause of death, and millions of people fall victim annually in developing and developed countries[24]. However, immediate medical attention is required to reduce the damage it causes. Diet, activity level, and lifestyle habits determine the level of risk intensity of stroke [7]. In medical technologies, AI, machine learning, and data science have been developed to detect diseases such as stroke more effectively and earlier so that clinicians can estimate a patient's risk of stroke based on a variety of patient data points [19, 22]. Traditional diagnostic tools such as MRI and CT scans are widely employed for stroke detection; however, the manual interpretation of these images remains time-consuming and prone to errors. Moreover, CNN-based models, which are commonly used in medical image analysis, face limitations in capturing the intricate spatial relationships across different brain regions, especially when abnormalities are subtle or distributed [3, 34].

Previous studies have used machine learning and deep learning algorithms, including artificial neural networks (ANNs), to predict stroke risk. However, CNN-based models, while effective, often fail to capture long-range dependencies in medical images and lack interpretability [1, 4]. Other diagnostic methods, such as MRI and CT scans, are commonly used for stroke detection, but they present challenges such as radiation exposure and test inaccuracies [34, 35]. Moreover, current machine learning approaches often produce opaque results, making it difficult to derive clear interpretations, thus limiting their clinical application [2]. To address the class imbalance, we applied techniques such as oversampling the minority class and data augmentation, ensuring a more balanced representation of stroke-positive and stroke-negative cases. This balancing was critical in improving the model's sensitivity to stroke features, as evidenced by the enhanced recall and F1 scores in our results.

The motivation for this research is driven by the increasing incidence of strokes worldwide, underscoring the urgent need for timely interventions that would limit disability and mortality under these conditions. Traditional methods to end strokes are time-consuming and tend to be erroneous, hence leading

[1]CAMs are visual explanations that highlight the regions of an image that the model focuses on when making a prediction, helping to improve interpretability.

to delayed interventions and worse patient outcomes. Several novelties are introduced in this article:

i. To improve patient outcomes and allow early intervention, the study's primary objective is to create a trustworthy machine learning model for predicting stroke illness.
ii. Addressing a major problem with unequal classes inherent in stroke prediction models, the study offers solutions to effectively tackle this challenge.
iii. The proposed model enhances stroke care and treatment by standardizing complicated models and combining local and global explainable approaches.

This research contributes by advancing the field of stroke diagnosis through the development of a model that combines the predictive power of deep learning with the interpretability required for clinical use. By addressing the limitations of previous CNN-based models and introducing a ViT-based architecture with CAMs, this study provides a more reliable and transparent method for stroke detection. This research builds on the existing literature while offering novel insights into stroke prediction using state-of-the-art machine learning techniques [17].

The paper is structured as follows: Section 2 reviews related literature, and Section 3 explains the development and testing of the proposed model. Section 4 presents experimental results and comparative analysis, followed by conclusions in Section 5.

II. Literature Review

Stroke is a major problem in global health as it occurs when the blood supply to the brain is interrupted or reduced, which causes brain tissue to experience a lack of oxygen. Among the many monetary costs associated with this cause of early death is the loss of productivity in Europe, which hit EUR 12 billion in 2017 and healthcare costs reached EUR 27 billion [15]. To predict strokes, a study [10] looked at machine learning methods. Stroke risk prediction using DT, SDG, KNN, SVM, and XGBoost classifiers was the focus of their work. A stroke was the top killer in the world in 2016, claiming 5.7 million lives, which accounted for 13% of all fatalities.

A. Machine Learning Techniques

Based on common traits or particular characteristics, a study [25] categorizes ML techniques for detecting brain stroke into four separate classes. A total of 39 papers were found in the Science Direct online research database about ML for brain stroke from 2007 to 2019. Results from ten studies examining stroke-related difficulties show that SVM models perform the best. Transfer learning algorithms have been applied to develop highly precise stroke risk detection models, utilizing historical data extracted from electronic medical records to forecast stroke likelihood among hypertensive patients [33].

B. Evaluation of Machine Learning Classifiers

The utilization of machine learning models, encompassing ensemble methodologies amalgamating diverse approaches, has demonstrated promising outcomes in pinpointing individuals at elevated risk of stroke [28]. The goal of this study[21] was to improve stroke prediction by investigating several ML approaches. Several approaches were examined, including Bayesian Classifier, Logistic Regression (LR), Decision Trees (DT), Random Forests (RF), and Multilayer Perceptron (MLP).

C. Advances in Deep Learning and Hybrid Models

A study [31] introduced an innovative diagnostic instrument targeting brain health. Their research comprised two key phases: classification and segmentation of brain stroke CT images. Presently, numerous studies leverage Deep Learning algorithms (DL), Machine Learning (ML) algorithms, and hybrid approaches integrating DL–ML techniques for brain stroke detection [8, 11, 36]. The classification task utilizes the hypercolumn technique [26] alongside Deep Convolutional Neural Networks [16]. Detection methods involve the dual-tree wavelet transform as discussed in [18]. Early disease diagnosis through thermography utilizing Gabor filters is presented in [32]. A comparison between artificial neural networks, particle swarm optimization algorithms, and CNNs is detailed in [13].

Furthermore, the classification of brain cancer employs the capsule neural network [14]. Using methods like conditional generative adversarial networks (CGAN), a study[5] sought to supplement databases containing information on stroke patients. Traditional deep learning models such as feedforward, CNN, bidirectional LSTM, and CNN-bidirectional LSTM were tested against their model, which relied on frequency features [12]. A study[30] demonstrated that their CNN-based DenseNet achieved 85.82% testing accuracy for stroke disease classification and prediction using ECG data collected from 12 leads.

D. Transfer Learning and Explainable AI

Transfer learning and explainable AI (XAI) are two prominent approaches that successfully use past data to forecast future events. This study[9] investigated how XAI may be used in healthcare IT to speed up patient diagnoses. Transfer learning techniques have demonstrated notable efficacy in swiftly and accurately predicting stroke outcomes.

The literature review highlights the significant role of machine learning (ML) in stroke prediction and diagnosis, showcasing algorithms like SVM and XGBoost that achieve over 80% accuracy. While ML holds promise for improving stroke treatment, further advancements in data processing and model interpretability are essential for enhancing stroke management.

III. Methodology

Baseline Method: The baseline paper [29] for this research presents a comprehensive analysis of various machine-learning algorithms for brain stroke detection, including logistic regression, random forests, and neural networks. This study serves as a basis for exploring more sophisticated methodologies.

This section describes the methodology and framework for designing a stroke detection model based on the Vision Transformer (ViT) architecture, specifically a more popular variant of the latter, known for easily capturing subtle spatial relationships in images.

A. Dataset

The dataset used in this study, sourced from [20], aimed to explore the risk factors associated with strokes, such as age, gender, smoking, diabetes, and high blood pressure. It included information from 100 stroke patients aged 16 and above, with 68% being male and 32% female. Each patient underwent brain CT scans, which were classified as normal or indicating a stroke. Initially, there were 1551 normal scans and 950 stroke scans. Notably, the normal scans were taken before the occurrence of strokes within the same individuals. All scans were grayscale and had dimensions of 650 × 650 pixels. To ensure effective model training without overfitting, the dataset underwent random equalization. This process resulted in a revised dataset containing 950 normal and 950 stroke images, each resized to 227 × 227 pixels. This balanced dataset facilitated robust analysis and modeling, providing insights into stroke risk factors while minimizing the impact of data imbalance.

B. Preprocessing

Data augmentation is one of the important techniques adopted to enrich the dataset and to enhance the model's ability in generalization. It would expose the model to various kinds of images both in normal and stroke cases by resizing, conversion to grayscale, normalization, and other techniques within the code.

Upscaling is one of the very basic preprocessing steps in code, aimed to standardize the size of images towards uniform processing across the dataset. Resizing all images to a uniform resolution of 227 x 227 pixels ensures that inputs for a model are all in uniform dimensions. Upscaling the images allows our model to detect finer details that are essential for accurate stroke identification, particularly in early stages or subtle cases.

Partitioning a dataset into a training set and a testing set is known as data splitting. The algorithm guarantees that the model gets trained on a big enough percentage of the dataset by randomly separating it into training and testing subsets while keeping another piece for assessment. By following this procedure, avoid overfitting and get an accurate intuition for how well the model will do on fresh, unknown data.

C. Proposed Model

Our proposed architecture of brain stroke detection is based on the ViT B-16 model as shown in Figure 1. Unlike traditional CNNs, which perform local feature extraction by convolutional filters, ViT B-16 makes use of self-attention in learning representations from the entire image altogether. We selected the ViT B-16 model due to its demonstrated balance between performance and computational efficiency in handling medical imaging tasks. Its architecture allows for efficient processing of high-resolution images while maintaining strong predictive power, making it particularly well-suited for stroke detection compared to other transformer model abnormalities.

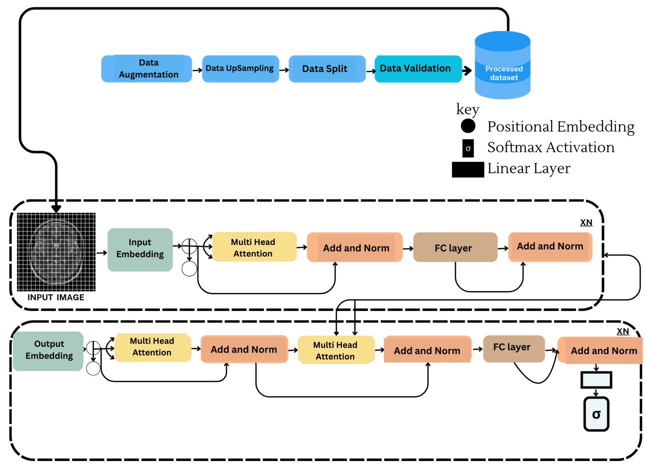

Fig. 1. System Model

Code utilizes the pre-trained ViT B-16 model from the vit_keras library. Here's a breakdown of how it integrates into the model. Pre-trained Weights, the model leverages the pre-trained weights obtained from training ViT B-16 on a large image dataset. These weights provide a strong foundation for feature extraction relevant to various visual recognition tasks, including brain stroke detection. Fine-tuning for Stroke Classification, While the pre-trained weights offer a good starting point, the final layer of the model is fine-tuned for the binary classification task of distinguishing between normal (label 0) and stroke-affected (label 1) brain scans.

D. Class Activation Maps (CAM) for Interpretability

In addition to the ViT B-16 architecture, our model leverages Class Activation Maps (CAMs) to enhance interpretability. CAMs provide a visual explanation of the model's predictions by highlighting the regions of the brain scan that contribute most significantly to the classification decision.

The generate_cam function takes three arguments:

- Model $\rightarrow$ Trained ViT B-16 model
- img_array $\in \mathbb{R}^{h\times w\times c}$ $\rightarrow$ NumPy array of brain scan image
- class_index $\in \{0,1\}$ $\rightarrow$ Predicted class index: 0 = normal, 1 = stroke

The function performs the following steps: Creates a sub-model, finds the gradients of the predicted class, averages the gradients across spatial dimensions, calculates a weighted sum of the feature maps, and processes the CAM to ensure valid values between 0 and 1.

1) CAM Visualization: The test image and its corresponding label (normal or stroke) are selected for visualization. The model then predicts class probabilities and the class with the highest probability is chosen. This visualization helps interpret the model's decision-making process, showing specific regions of the brain scan that influence the classification.

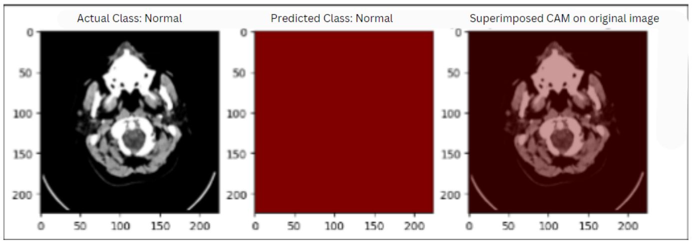

Fig. 2. Visualization of Brain MRIs with Class Activation mapping

In stroke detection, CAMs can reveal areas with hyperintensities, hemorrhages, or other stroke-related abnormalities that guide the model's predictions. This approach, combined with the ViT B-16 architecture's ability to capture global features, enhances model interpretability and supports clinical decision-making by making the reasoning behind the predictions clearer.

IV. RESULTS

This section describes a detailed comparison of our proposed model Vision Transformer model (ViT B16) in contrast with the other existing state-of-the-art models for detecting a brain stroke. In particular, we compare performance using a variety of standard Metrics such as accuracy, precision, recall, F1 score, and dice score. Finally, we discuss insights obtained from the confusion matrix and ROC curve generated during the evaluation of our proposed model. In other words, the collective samples for all the tests used in this analysis were 100.

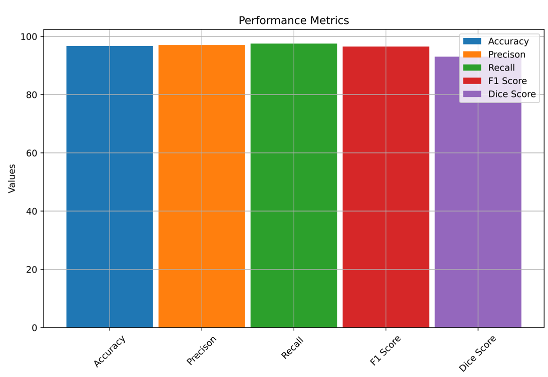

Fig. 3. Performance Metrics for Brain Stroke Detection

As illustrated in figure 3, the ViT B16 model achieved remarkable performance across all key metrics. The accuracy reached 96%, with a precision of 97%, recall of 97.5%, F1 score of 96.5%, and a Dice score of 93%. These results demonstrate the model's robustness in detecting stroke-affected regions in brain scans. The high recall rate, in particular, is crucial in medical diagnostics.

Figure 4 shows the confusion matrix that provides more insight into this model. Of the total of 100 test samples, there were 96 true negatives (healthy individuals) and 97 true positives (stroke cases) with 3 false positives and 2 false negatives. The model achieved 97 true positives, correctly identifying stroke cases, and 96 true negatives, accurately detecting healthy patients.

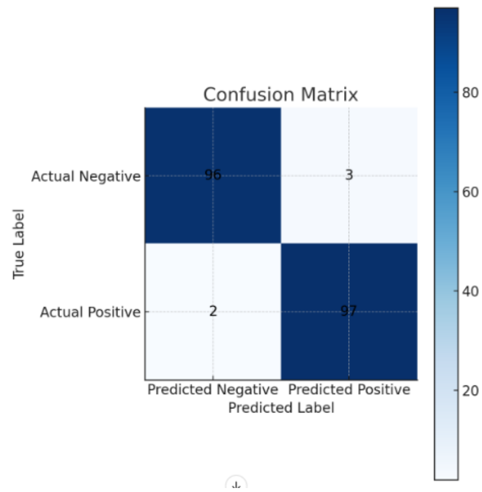

Fig. 4. Confusion Matrix for Vision Transformer

The Receiver Operating Characteristic (ROC) curve, shown in Figure 5, is essential for balancing sensitivity and specificity. With an Area Under the Curve (AUC) of 0.97, the model demonstrates strong discrimination power, effectively differentiating between stroke-positive and healthy cases.

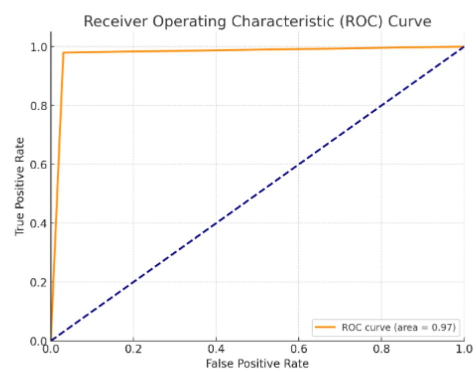

Fig. 5. Performance Evaluation of the Vision Transformer via ROC Curve.

The comparative analysis in Table I demonstrates how our ViT B16 model outperforms previous state-of-the-art approaches. Our model achieves an accuracy of 96%, surpassing all previous methods. The improvements in precision, recall, and F1 score further demonstrate the superior performance of the ViT B16 model. For example, compared to [36], which achieved an accuracy of 93% and F1 score of 94%, our model improves both accuracy and F1 score to 96% and 96.5%, respectively.

CAM projection depicts regions within brain MRI images that the model focuses on to provide differentiation between stroke-positive and stroke-negative cases.

TABLE I
COMPARATIVE ANALYSIS OF RESULTS WITH PREVIOUS STATE-OF-THE-ART STUDIES

Studies	Accuracy	Precision	Recall	F1 Score
Sailasya et.al., [23]	78.00	77.50	77.68	77.50
Tursynova et.al., [27]	81.00	82.50	83.00	81.50
Santwana et.al., [6]	87.22	87.00	90.00	90.65
Wang et.al.,(Baseline Method) [29]	70.00	70.00	70.00	70.00
Our Results	**96.00**	**97.00**	**97.50**	**96.50**

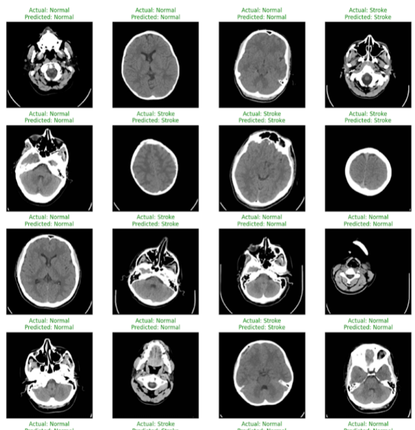

Fig. 6. Stroke Prediction Model Performance.

Strong activation of affected regions by stroke and low activity of healthy regions describe the model as functioning well for discrimination purposes. Visualizations from the class activation map can also help analyze the misclassifications, giving insights into why the model missed or misclassified some of the cases.

This section indicates promising avenues in stroke detection based on a model like ViT B16. Its sheer precision, recall, and F1 score make it an excellent tool to be used in the clinic, giving an early and accurate diagnosis. Further research might extend the dataset to cover a greater variation of cases of patients that would then lead to broader applicability and generalization across different demographics.

V. CONCLUSION

Using the architecture of ViT B16 that captures the complexity of spatial relations in images, this research detects a stroke model using a dataset of brain CT scans. Data augmentation, normalization, and scaling were applied by the research. The novelty of the method proposed by ViT to consider images as a sequence of patches made it possible to surpass traditional CNNs as accuracy results are quite high and subtle anomalies are detected effectively.

Future work aims to optimize ViT for diverse datasets to enhance generalizability, explore multi-modal data integration (e.g., CT and MRI), and develop lightweight models for mobile health. Refining CAM visualizations and real-time clinical integration will further validate its practical impact. This approach. Although Vision Transformers show a great ability in the detection of brain stroke, in reality, within healthcare facilities, there are several challenges for the practical use of such systems. ViTs require an immense amount of computation, which is usually unavailable in low-resource or remote medical settings.

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