VGG16-based Brain Stroke Prediction in CT Scan

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Abstract
Brain strokes pose a significant global health challenge, ranking as the second leading cause of mortality worldwide. In India, reports indicate a frequency of three stroke incidents per minute. Ischemic strokes, resulting from arterial blockages, constitute about 80% of cases, with hemorrhagic strokes, caused by blood vessel ruptures, making up the remaining 20%. This study explores the integration of Generative Adversarial Networks (GANs) and the VGG16 model for brain stroke detection. GANs, known for their ability to generate diverse medical images, are used to augment the training datasets for machine learning models. The VGG16 architecture, recognized for its deep convolutional layers, is employed for robust feature extraction, crucial for stroke identification. By combining GAN-synthesized data with VGG16-based classification, the proposed methodology aims to enhance the accuracy of stroke detection from brain scans. This innovative approach holds promise for improving early stroke detection, enabling timely intervention, and ultimately enhancing patient outcomes.

Keywords: Brain Stroke, Machine Learning, Generative Adversarial Networks, Visual Geometry Group 16

1. Introduction
A brain stroke is a serious medical emergency that occurs when there is a disruption in the blood supply to the brain. This can happen due to blockage in the blood vessel (ischemic stroke) or rupture of the blood vessel (hemorrhagic stroke). Strokes are a worldwide critical health concern and can have severe and often irreversible consequences. Brain strokes can cause severe damage to the brain. Early detection is crucial for effective treatment. When machine learning algorithms are used to analyze brain images and identify strokes, a quick and accurate diagnosis can be performed. This can help doctors make informed decisions about treatment options and improve patient outcomes. By generating synthetic data, it expands the training dataset, improving the robustness of the Ml model.

The development of a brain stroke detection system employing machine learning (ML) and generative adversarial networks (GAN) represents a significant advancement in medical technology. Machine learning plays a pivotal role in the system by analyzing complex data patterns within medical images, such as CT scans. The integration of generative adversarial networks (GANs) further elevates the system's capabilities. GANs consist of two neural networks, which are generators and discriminators. These two are engaged in a continual adversarial training process. The system typically involves a combination of medical imaging, data analysis, and machine learning techniques.

2. Literature survey

The paper "A BrainNet (BrN)-based New Approach to Classify Brain Stroke from CT Scan Images" introduces a method for classifying brain stroke from CT scan images using a hybrid model called BrainNet (BrN). The proposed model combines convolutional neural network (CNN) and support vector machine (SVM) algorithms, resulting in an accuracy score of 91.91%. The proposed system uses deep learning models to detect and classify brain strokes from images. The system achieves high accuracy in detecting and classifying brain strokes from medical images. The system is effective, low-cost, and saves significant time [1].

The research paper "Risk Factor Identification for Stroke Prognosis Using Machine-Learning Algorithms" identifies and ranks the key risk factors associated with stroke using advanced machine learning (ML) models, which helps in developing effective prevention and management strategies. The research evaluates the performance of ten ML classification models, including Random Forest (RF), Extreme Gradient Boosting (XGB), Support Vector Machine (SVM), Decision Tree (DT), Light Gradient Boosting Machine (LGBM), Cat Boost Classifier (CBC), Ada Boost Classifier (ABC), Multi-Layer Perceptron (MLP), K-Nearest Neighbors (KNN), and Logistic Regression (LR). The comparison of results is conducted using various performance evaluation metrics such as accuracy, F1-score, precision, recall, and ROC_AUC. [2]

The article introduces an approach to detect ischemic brain strokes from MRI scans using a logistic regression classifier. The model attains an accuracy rate of 96%, with a sensitivity of 92.3% and a specificity of 100%. The proposed method comprises essential stages. Initially, the MRI images undergo preprocessing to diminish noise and transform into grayscale. Subsequently, specific sections indicating strokes in the MRI grayscale images are isolated using the hue, saturation, and value (HSV) color threshold. These segmented images of stroke regions are then converted into binary images, minimizing computational intricacies. [3]

The paper "Machine Learning Algorithm for Stroke Disease Classification" presents a comprehensive study conducted at Politeknik Elektronika Negeri Surabaya, Indonesia, focusing on the preprocessing of CT scan image data of stroke patients to improve image quality and reduce noise. The primary objective of the study is to apply machine learning algorithms to classify patients' images into two sub-types of stroke disease: ischemic stroke and hemorrhagic stroke. The system design used in this study consists of three main stages: data collection, pre-processing data, and the performance analysis method of classification. The study employed eight machine learning algorithms for stroke disease classification, namely K-Nearest Neighbors, Naive Bayes, Logistic Regression, Decision Tree, Random Forest, Multi-layer Perceptron, Deep Learning, and Support Vector Machine. The results of the study revealed that the Random Forest algorithm achieved the highest level of accuracy at 95.97%, along with precision values of 94.39%, recall values of 96.12%, and f1-measures of 95.39%. [4]

The article provides a detailed analysis of generative adversarial networks (GANs), covering their history, theory, characteristics, changes, measures, implementations, disadvantages, and prospective scope. It discusses a range of GAN implementations, including human pose estimation, text mining, and image generation. The authors emphasize the need for addressing current issues and weaknesses in GANs, such as unstable planning, non-convergence, and the requirement for more computer resources. The article also discusses the challenges of using GANs in non-image data applications, such as natural language processing, due to differences in data quality. Additionally, it addresses concerns about the potential misuse of GANs for creating fraudulent images and videos and highlights initiatives aimed at combating such misuse. [5]

The paper presents the use of supervised machine learning (ML) algorithms to classify brain MRI reports and identify patients with acute ischemic stroke (AIS). The study involved analyzing 3,204 brain MRI documents, of which 432 (14.3%) were labeled as AIS. Descriptive analyses were performed to compare the character lengths of AIS and non-AIS reports, and a Mann-Whitney U test was used for comparison. Additionally, a "keyness plot" was utilized to determine word frequency in AIS and non-AIS reports. [6]

The paper presents a novel approach for the automated detection of acute ischemic stroke (AIS) using CT angiography (CTA) images. The proposed model, DeepSymNet, is designed to leverage the visible differences between the two hemispheres of the brain in CTA images, both in terms of vasculature structures and voxel intensities in the tissue affected by the stroke. The model aims to robustly compare the two hemispheres to identify if a patient has suffered from AIS without requiring the specific location of the affected areas. The performance of DeepSymNet is evaluated using metrics such as balanced accuracy, area under the ROC curve (AUC ROC), sensitivity, and specificity. The results demonstrate that the model outperforms baseline methods in terms of classification accuracy and sensitivity, achieving an AUC of 0.914 and demonstrating promising capabilities for AIS detection.[7]

The paper titled "GAN-Based Synthetic Brain MR Image Generation" presents a novel approach for generating realistic medical images, with a specific focus on brain MR images. The study addresses the challenging goal of creating synthetic medical images that are visually indistinguishable from real ones, which could significantly improve diagnostic reliability, enable data augmentation in computer-assisted diagnosis, and facilitate physician training. The proposed GAN-based image generation approach involves pre-processing the images and training the GANs to produce high-quality synthetic images. The authors conducted preliminary validation using a Visual Turing Test, where even an expert physician was unable to accurately distinguish the synthetic images from real samples. This indicates the high level of realism achieved by the synthetic images generated using GANs.[8]

3. Proposed Method

A. System Design

The proposed approach is designed to classify the Brain Stoke disease from the collected dataset. It starts by gathering a collection of images that represent brain stroke. These images are then processed to highlight key features and ensure they're all the same size for consistency. Next, it builds a algorithm called a Convolutional Neural Network (CNN) using VGG16 pretrained model, that learns to recognize patterns in these images. The CNN goes through several rounds of training to get better at identifying signs of stroke. During training, the system checks its progress regularly to make sure it's learning correctly. It also sets aside some images it hasn't seen before to test itself later and make sure it's not just memorizing things. After training, the system evaluates its performance on the new images it set aside, checking things like accuracy and how well it identifies different types of strokes.

B. Block Diagram

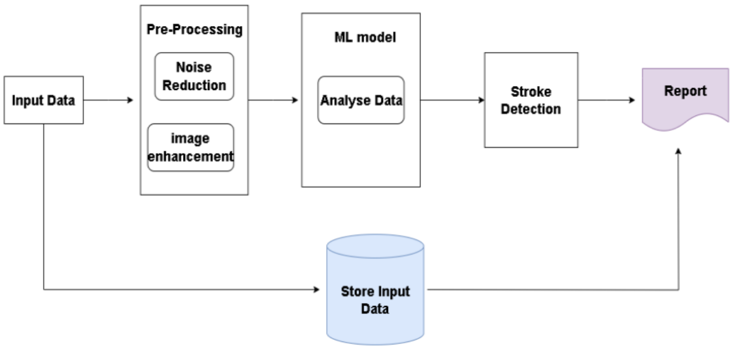

Figure 3.1: Block Diagram

C. GAN Model

The system's goal is to create synthetic medical imaging data, CT scans, using GANs. These artificially generated images, when combined with real patient data, form a diverse dataset covering various stroke-related patterns. To ensure accurate stroke detection, the process involves training a neural network to generate synthetic data that closely resembles real patient data. Here, two neural networks, the generator and the discriminator, engage in a sort of competition. The generator creates fake data, while the discriminator helps to tell it apart from the real data. Over time, this helps the generator learn to produce data that's nearly indistinguishable from the real stuff, leading to a high-quality dataset.

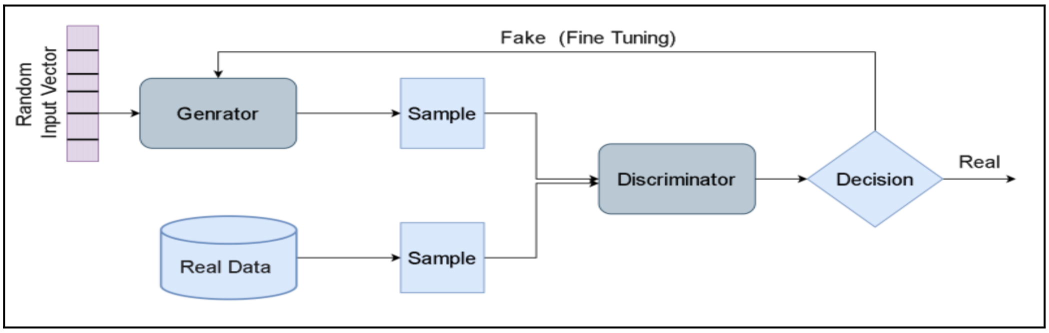

Figure 3.2: GAN Architecture

D. Mathematical Model

1. Input the CT scan images.
    - Input data converting into Grey image and defining single size (Training Data, Validation Data, Testing Data).
2. Three Convolutional Layers
    - Activation('relu')
    - MaxPooling2D(),
    - Dropout(),
    - Flatten(),
    - Dense()
3. Compile the model
    - Loss('binary cross entropy'),

- Optimizer('adam')
4. Fit the model for Training Data and Validation Data with 100 epochs
5. Evaluate the model
   - Accuracy
   - Loss
   - Confusion Matrix
   - ROC curve
6. End

4. Dataset Description

From Table.1 there is 4822 stroke data haven used to predict the stroke in ct scan. Here, 1072 data are of Hemorrhagic brain stroke, 1551 data are of ischemic brain stroke, 1551 data are of normal brain data. Of which 3085 data are used for training, 772 data are used for validation, and 965 data are used for testing. CNN models are applied to find out the models' best model stance, and best fit for the dataset collected from Kaggle.

	Hemorrhagic Stroke	Ischemic Stroke	Normal
Training Data	1069	1025	991
Testing Data	365	271	329
Validation Data	286	255	231

Table 4.1

5. System Operation

In the machine learning process for identifying potential strokes in brain scans, The model prepares the collected data through a careful cleaning and standardization process. This step ensures that the information is in a suitable form for deeper analysis. Techniques for feature extractions. Preparing data and extracting meaningful aspects from the medical images like shapes, textures, and varying intensities found within the images. It utilizes a dataset comprising images representing various aspects of brain health, categorized into different classes. These images undergo preprocessing steps to ensure uniformity, including resizing and normalization.

The system architecture is built around the integration of the VGG16 CNN algorithm, short for Visual Geometry Group 16, is a deep convolutional neural network which consists of 16 weight layers, including 13 convolutional layers and 3 fully connected layers. for brain stroke detection. The VGG16 CNN model is then constructed, featuring multiple convolutional and pooling layers to extract and learn intricate features from the input images.

Training the VGG16 CNN model involves optimizing its parameters using techniques like gradient descent, adjusting them iteratively to minimize prediction errors. During training, the model learns to classify images into the categories, ischemic stroke, hemorrhagic stroke and normal brain scan.

Validation and testing phases follow, where the model's performance is evaluated on unseen data to assess its accuracy and generalization ability.

The system utilizes Python-based libraries and frameworks such as TensorFlow and Keras to develop and train the VGG16 CNN model for image processing task.

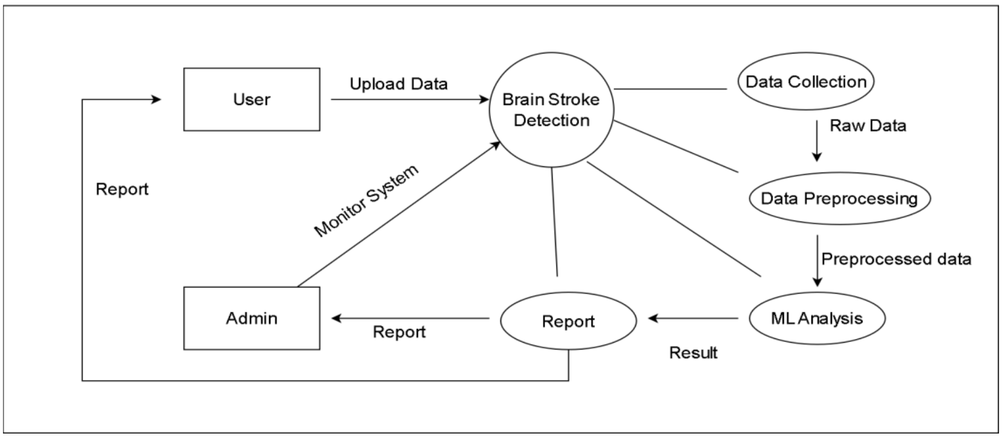

Figure 5.1: System Operation of the Proposed System

6. Evaluation

We used Convolutional Neural Network to train images of size 256 × 256 × 3. The keras Sequential model is used for neural layers. Conv2D layers are fundamental building blocks in CNN architectures. There have used 100 epochs to train the proposed model. After Training the models, it provides different performances shown.

Accuracy of model is as shown in Figure 6.1. Accuracy of model provides how well the model is learning from the training data. Accuracy is represented as:

$$Accuracy = \frac{NumberofCorrectPredictions}{TotalNumberofPredictions} \times 100$$

The loss function of model is as shown in Figure 6.2, It provides a quantitative measure of how well the model is performing during training. Lower values of loss indicate that the model's predictions are closer to the true labels in the dataset, reflecting better performance.

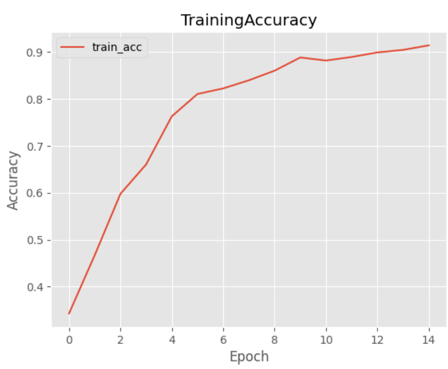

Figure 6.1: Accuracy

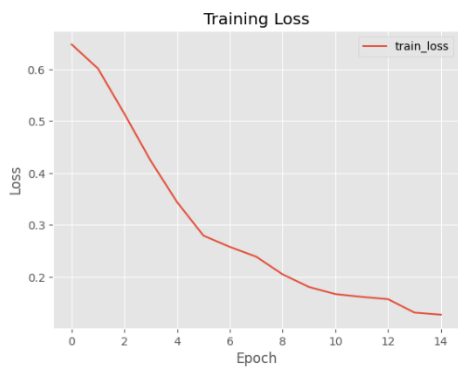

Figure 6.2: Loss

The confusion matrix of model is as shown in Figure 6.3, provides tabular representation of the performance of classification model, presenting a summary of the predicted and actual classes for a dataset. And used for evaluating the performance of model.

- True Positive (TP): Instances where the model correctly predicts the positive class.
- True Negative (TN): Instances where the model correctly predicts the negative class.
- False Positive (FP): Instances where the model incorrectly predicts the positive class when the actual class is negative (Type I error).
- False Negative (FN): Instances where the model incorrectly predicts the negative class when the actual class is positive (Type II error).

Receiver Operating Characteristic (ROC) curve for model is as shown in Figure 6.4. is a graphical representation used to evaluate the performance of classification model across different threshold settings. It plots the true positive rate (TPR) against the false positive rate (FPR).

True Positive Rate (TPR), also known as recall, is the ratio of correctly predicted positive instances to all actual positive instances.False Positive Rate (FPR) is the ratio of incorrectly predicted positive instances to all actual negative instances.

$$TPR = \frac{TP}{TP + FN}$$

$$FPR = \frac{FP}{FP + TN}$$

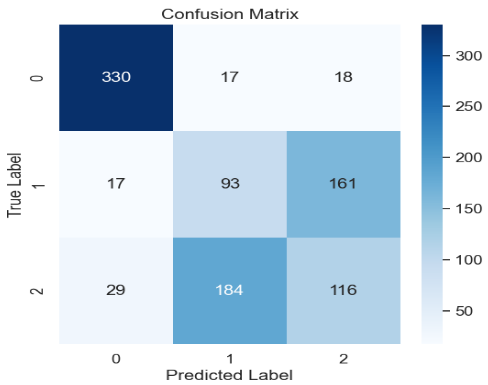

Figure 6.3: Confusion Matrix

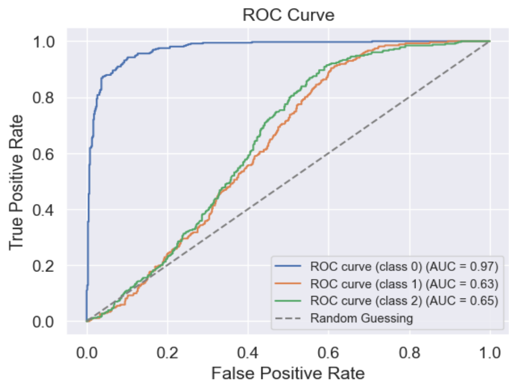

Figure 6.4: ROC Curve

7. Conclusion

The integration of the VGG16 model with machine learning methodologies for brain stroke detection shows a significant advancement in medical imaging technology with profound implications for patient care. Addressing issues such as the availability of limited and heterogeneous datasets and ensuring compliance with regulatory standards necessitates attention to detail and robust quality assurance measures. Using GAN for synthetic images the dataset became vast for training testing the model. This approach provides higher accuracy and efficiency of system which is important in the field of medical science. The VGG16 model, with its deep convolutional layers and robust feature extraction capabilities, can effectively analyze complex medical imaging data and identify subtle patterns indicative of stroke with high precision. Moreover, navigating the complexities of algorithm interpretability, ethical considerations, and the imperative for real-time processing demands a judicious balance between technological innovation and ethical responsibility. The transformative applications of the VGG16 model in brain stroke detection, including real-time diagnostics and continuous patient monitoring, underscore its pivotal role in advancing the field of medical imaging This.

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