Brain Stroke Prediction Using Visual Geometry Group Model

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Abstract: Stroke has become the leading cause of high mortality and disability rates in the modern era. Early detection and prediction of stroke can significantly improve patient outcomes. In this study, we propose a deep learning approach using the Visual Geometry Group (VGG-16) model. VGG-16 is a type of Convolutional Neural Network (CNN) which is one of the best computer vision models to date to predict the occurrence of a stroke in the brain. VGG-16 is a type of CNN that is one of the best computer vision models to date. We used a dataset consisting of Magnetic resonance imaging (MRI) images of patients with and without stroke. The VGG-16 model was pre-trained on the ImageNet dataset and fine-tuned on our dataset to predict the occurrence of a stroke. Our experimental results demonstrated that the proposed approach achieves high accuracy and can effectively predict stroke occurrence. We have also conducted an extensive analysis of the model's performance and provided insights into important features used by the model to predict stroke occurrence. The proposed approach has the potential to be used in clinical settings to aid in the early detection and prevention of stroke.

1 INTRODUCTION

Stroke is a devastating illness that affects millions of people around the world. According to recent estimates, over 15 million individuals suffer from this condition every year. While it is true that stroke is a major health concern in the United States, with one person experiencing it every four minutes, this is also a worldwide problem. Stroke is a leading cause of death and disability on a global scale, with about 6 million individuals dying from it and another 5 million being left permanently disabled. Clearly, more needs to be done to prevent and treat this debilitating illness (WSO, 2022).

A medical emergency commonly referred to as a brain stroke, brain attack, or cerebrovascular accident (CVA), occurs when the blood supply to the brain is interrupted. This can be caused by a blockage or rupture of a blood artery in the brain. When blood flow is compromised, brain cells start to die due to a lack of oxygen and nutrients. This can result in irreversible brain damage, disability, or even death. There are two primary subtypes of stroke: hemorrhagic stroke and ischemic stroke. A hemorrhagic stroke occurs when a blood vessel in the brain bursts and causes bleeding, while an ischemic stroke occurs when a blood clot blocks an artery in the brain (A. Kumar, et al., 2023).

High blood pressure, smoking, diabetes, high cholesterol, obesity, and a family history of stroke or heart disease are some variables that can increase the risk of stroke. Lifestyle choices such as poor diet, inactivity, and stress are also stroke risk factors. Public education and awareness initiatives can help reduce the incidence of stroke by promoting healthy lifestyle choices and encouraging individuals to seek early medical assistance if they experience stroke symptoms (R. R. Bailey, 2016). Figure 1 shows the different type of brain strokes.

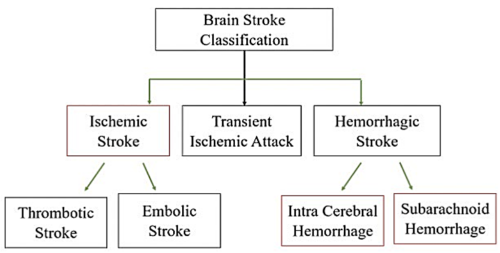

Figure 1: Brain Stroke Types – The diagram above addresses the different types of strokes that can affect a human brain.

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Artificial intelligence (AI) has advanced significantly in recent years, with applications in everything from autonomous vehicles and medical diagnostics to voice and image recognition. The advancement of deep learning, a branch of machine learning that has made strides in a variety of AI applications, has been a major force behind this development. We go over the fundamentals of deep learning, its uses, and its possible social effects in this paper.

Deep learning is a vital component of Artificial Intelligence, which uses artificial neural networks to model and solve complex classification problems. These artificial neurons, which function as the processing and transformation units of these neural networks, are organized into numerous layers of interconnected nodes. Deeper layers of neurons learn to recognize increasingly abstract and complicated patterns as they learn to recognize and extract different characteristics of the data.

Deep Learning has the capacity to learn and improve on its own, without being explicitly programmed. By processing large amounts of data and identifying patterns and relationships within that data, deep learning algorithms can learn to perform complex tasks such as image and speech recognition, natural language processing, and even game playing.

In healthcare, deep learning is being used to develop diagnostic tools to analyse medical images and data to detect diseases such as cancer and Alzheimer's (I. M. Sheikh and M. A. Chachoo, 2022). These tools have the potential to improve the accuracy and speed of diagnosis, enabling earlier detection and better outcomes for patients (L Chen, et al., 2023; P Bentley, et al., 2014).

Yoon-A Choi et al. proposed a system for predicting the likelihood of stroke based on real-time bio-signal data using neural networks. 3,322 electroencephalogram (EEG) and (electrocardiogram) ECG signals were collected from stroke patients and healthy individuals. The proposed model is a Convolutional Neural Network (CNN), which extracts features from the signals and a long short-term memory (LSTM) network that models temporal dependencies. This system gave a model accuracy of - 93.9 percent and a sensitivity of 96.7 percent (Y-A Choi, et al., 2021). This research however needed further research to validate the system's effectiveness in larger and more diverse populations.

Vivek S Yedavalli et al. discussed the potential applications of artificial intelligence (AI) in stroke imaging, including diagnosis, treatment selection, and prognosis prediction, using different machine learning models and neural networks. Models like Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Recurrent Neural Networks (RNN), Support Vector Machines (SVM), and Random Forest (RF) were trained, and their accuracies were compared to select the best model. It was shown that CNN had the highest accuracy at 91 percent. This study used 4 different datasets, namely, MRI-GENIE, STRIDE, MR CLEAN, and TRACK-TBI (B B Ozkara, et al., 2023).

Hilbert et al. proposed a deep learning model for predicting the outcome of endovascular treatment in patients with acute ischemic stroke. The dataset was a collection of 92 patients who underwent endovascular treatment for acute ischemic stroke and were divided into a training set of 60 patients and a test set of 32 patients. To improve its performance on the outcome prediction task, the deep learning model was trained on a small subset of the training set (n=10) utilizing transfer learning and fine-tuning approaches. The model was then assessed using the test set and the remaining training data. This proposed system used the VGG-16 model. The model was then fine-tuned on the training data using a transfer learning approach, which involves using the pre-trained weights of the VGG-16 model and training the final layers on the task-specific dataset. This gave an accuracy of 80 percent (A Hilbert, et al., 2019).

Sonavane et al. presented a method for detecting brain stroke using convolutional neural networks (CNNs) and deep learning models. This is a novel approach that combines CNNs with deep learning models to automatically see brain strokes from computed tomography (CT) images. The dataset is a collection of 250 CT images, including 150 healthy and 100 stroke images, which were used to train and evaluate their deep-learning models. The methodology tested four different deep learning models, including a CNN, a deep belief network, a stacked autoencoder, and a convolutional autoencoder, to determine the most effective model for detecting brain stroke. The CNN model achieved the highest accuracy at 97.6 percent for detecting brain stroke, followed by the stacked autoencoder model with an accuracy of 94.8 percent. The authors also performed a comparative analysis with existing methods and found that their proposed method outperformed existing methods for brain stroke detection. This proposed system's future research could explore the use of larger datasets and more advanced deep learning models to further improve the performance of the brain stroke detection system (B R Gaidhani, et al., 2019).

Mahadevan et al. compared the performance of traditional hand-crafted features and convolutional neural networks (CNNs) for diagnosing stroke from retinal images. The dataset that was used in this proposed system contained 450 retinal images, including 150 healthy, 150 hypertensive, and 150 diabetic images, to train and evaluate their models. The methodology involved in this method comprised of testing two different approaches: traditional feature extraction using hand-crafted features, and deep learning using a CNN. The results of the study showed that the CNN achieved significantly better performance than the traditional feature extraction method, with an accuracy of 96.5 percent compared to 87.3 percent for the hand-crafted features. The authors also compared the two approaches and found that the CNN had higher sensitivity, specificity, and F1 score for diagnosing stroke from retinal images (R S Jeena, et al., 2021).

Amitava Nag and his research group did another research to predict the brain stroke. They applied Ada-Boost and other boosting methods to investigate and classify the information of more than 48000 patients achieving high accuracy (S. Mondal, et al., 2023). The main difference between the current and Nag's project is the type of data. We worked on image data.

In the other similar project, Sachin and Vishal Jain classified brain tumours with deep learning models with 98% accuracy. The applied 5, 10 and 20 cross validation folds to realize high accuracy (S. Jain and V. Jain, 2023). Our project predicts the brain stroke with Neural Network models.

Emotion recognition project using VGG-16 model accomplished by Srindhar and his research group in 2023 (S. Vignesh, et al., 2023). Sunil Kumar et al, applied random forest and VGG-16 methods to classify bell pepper leaf disease with LBP features (M. Bhagat, et al., 2023).

Other researchers applied VGG-16 method to classify and predict different types of diseases and syndromes, with different type of dataset, and accuracy. What makes our project different is that we predict brain stroke using image data with high accuracy. For this aim we applied different methods, which VGG-16 predicted the stroke with highest accuracy among other methods. We worked on a large image dataset.

2 DATA DESCRIPTION

The dataset used for this project is collected from Kaggle*, an online community, with millions of diverse datasets available for analyses. We chose a collection of medical images, specifically computed tomography (CT) images, of the brain of individuals who have experienced a stroke and of individuals who have not experienced a stroke. There are a total of 2,501 images in the datasets out of which 1,551 belong to individuals who have not experienced strokes and the remaining 950 belong to individuals who have experienced a stroke. This is a binary classification problem where images belong to two different classes.

3 METHODOLOGY

3.1 Data Pre-Processing

The final image size of the input dataset for the VGG-16 (Visual Geometry Group) model is 256x256 pixels. In the next pre-processing step we split our dataset into training (80 percent), testing (10 percent), and validation (10 percent) sets. To include more samples in our dataset we implemented an image data generator that creates different variations of each image at each epoch. The variations include random image rotations, horizontal flips, and shifts. Additionally, zoom and brightness effects are set in the range of 0.2 and 0.8. After the pre-processing steps, the transformed images are used by the VGG-16 model to predict stroke.

3.2 Baseline Model and Methodology

The VGG-16 model which is a 16-layered deep image classification convolutional neural network (CNN) architecture is the baseline model in our research. It is one specific variation of a Convolutional Neural Networks (CNN), originally proposed by Simonyan and Zisserman (K Simonyan and A Zisserman, 2019). This CNN was chosen in this study based on its prior success at image recognition. While many variations exist for CNN, using a configuration that has been previously validated enables achieving optimal results. The VGG-16 model differs from other configuration in its choice of convolutional layers, pooling layers, and dense layers. In all, VGG-16, has 16

* https://www.kaggle.com/datasets/afridirahman/brain-stroke-ct-image-dataset

convolutional layers. These are the layers where learning occurs. This specification facilitates up to 138 parameters that can be trained. The 16 convolutional layers are divided in 5 groups, each with a pooling layer at the end. At the end of the stack of layers there a three dense layers. In all, VGG-16 has 21 layers. In addition to the predefined layers in the CNN, VGG-16, the convolution layers are relatively small, with 3x3 filters with a stride of 1.

The pre-trained VGG-16 model classifies over 1000 images from different categories. We incorporated the VGG-16 model into our sequential model with several flattened, dense and output layers. The output layer consists of a sigmoid activation function, which is used for binary classification that consists of two classes i.e. stroke and non-stroke. Model training was done on 25 epochs and a batch size of 32. The final sequential model used a monitoring metric called early stopping that halts the training process when there is no further improvement in learning.

In this proposed system, we use 'Adam' optimizer for our model because the Adam optimizer dynamically adjusts for each parameter based on the first and second moments of the gradients, which increases the efficiency of the model performance and simultaneously, requires low storage space. We calculate the loss by the binary cross-entropy metric, which computes gradients correctly and encourages classification with high accuracy rate.

The model also makes use of early stopping, which creates an early stopping call back that monitors the validation accuracy and stops the training process if the accuracy does not improve for a specified number of epochs.

4 RESULTS

During the first epoch, the training accuracy started at 61 percent which increased significantly to 83 percent at the end of the 25th epoch. While predicting outcomes on the test dataset, the model was able to correctly predict over 80 percent of the outcomes. Since the difference between the training and test accuracies is not too high, we can say that the model is not prone to overfitting.

From the classification report, the precision for people with no brain stroke is 0.90, and for the people with brain stroke is 0.77. This means that there are more people not detected with brain stroke and fewer people with brain stroke.

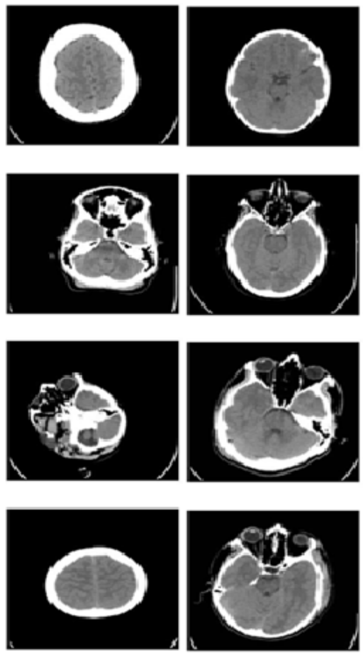

Figure 2: Brain Stroke Detection – The left image represents the images with no brain stroke and the right-side image represents images with the prediction of a brain stroke.

Figure 2 portrays the difference between a normal brain and a brain that has stroke. The image on the left side represents the scans of the patients with no stroke prediction and the images in the right side are that of the people who have experienced a brain stroke.

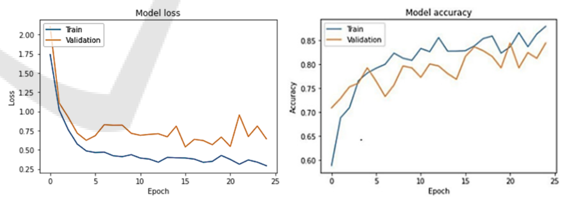

Figure 3: The AUC for Training Vs Validation Loss.

Figure 3 is a graphical representation of the performance of the Visual Geometry Group Model during the training and validation phases. This measures the model's ability to correctly classify data points. It is plotted against the number of epochs of the training process. The image on the left represents the model loss and exhibits that the model performed well without any overfitting until the 5th epoch, as the training and validation loss are close enough to each other. The image on the right represents the model accuracy, which measures the overall performance of the model.

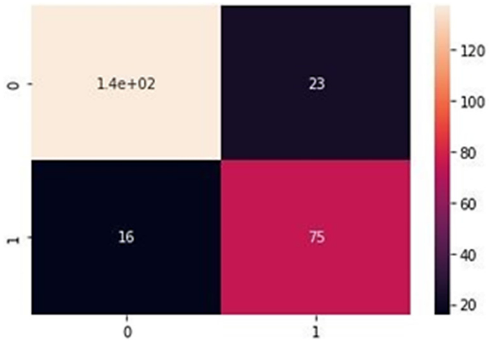

Figure 4: Confusion Matrix.

Figure 4 is a confusion matrix, that compares the actual and predicted values of the model on the given dataset. The confusion matrix displays the least number of true positives. The number of true negatives is more than the number of true positives, which means that there are more predictions for people with brain stroke.

	precision	recall	f1-score	support
0	0.90	0.86	0.88	160
1	0.77	0.82	0.79	91
accuracy			0.84	251
macro avg	0.83	0.84	0.83	251
weighted avg	0.85	0.84	0.85	251

Figure 5: Classification Report.

Figure 5 portrays the classification report and provides a detailed evaluation of the model's ability to correctly classify instances as is typically used in classification tasks where the goal is to predict the class of the given dataset. The proportion of the positive predictions that actually had stroke is 0.90 and the proportion of actual positive instances that were correctly identified by the model is 0.86.

5 CONCLUSION

In conclusion, the VGG-16 model shows promising results in predicting the occurrence of brain stroke using medical imaging data. Our research demonstrates that the VGG-16 model can achieve high accuracy of 80 percent in predicting the likelihood of stroke by analysing the images of the brain without overfitting. However, further research is needed to improve the accuracy and generalizability of the VGG-16 model, as well as to explore its potential for other medical imaging applications. Additionally, it is important to address ethical and privacy concerns related to the use of patient data in developing and deploying AI models for medical diagnosis. Overall, our research suggests that the VGG-16 model has significant potential as a tool for predicting brain stroke using medical imaging data and underscores the importance of continued research and development in this area.

6 FUTURE SCOPE

In this project we applied neural networks to predict the stroke. In the next project we apply another prediction and image analysis methods to validate our results with higher accuracy. There is a plan to develop a platform to upload images and define the possibility of brain stroke.

Data Availability

The dataset used for this project is collected from Kaggle. https://www.kaggle.com/datasets/afridirahman/brain-stroke-ct-image-dataset.

Conflict Interest Statement

There is no conflict of interest declared by authors. All authors have reviewed and agreed with manuscript. We state that the submission is original paper and is not under review at any other journal.

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Ethical Approval

All subjects gave their informed consent for inclusion before they participated in the study.

Consent to Participate

Authors consent to participate in this project and we know that: the research may not have direct benefit to us. Our participation is entirely volunteer. There is a right to withdraw from the project at any time without any consequences.

Consent to Publish

We give our consent for the publication of exclusive details, that could be included figures and tables and details within the manuscript to be published in Computational Brain & Behavior.

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