**ANALYSING BRAIN TUMOR DETECTION USING VGG-16 AND VGG-19**

**TO ENHANCED ACCURACY**

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**ABSTRACT**

This paper hopes to show whether V G G-16 and V G G-19 are effective in accurately diagnosing whether a brain has (or hasn't) undergone tumorous changes when viewing M R I images. **MATERIALS AND METHODS:** The dataset consists of 4500 images taken from patients' brains with MRI scans. There are both normal cases and those with tumors. We use data preprocessing tools and image augmentation techniques to optimize model performance. In order to rectify this situation, a five-fold cross-validation approach using VGG-16 and VGG-19 models is adopted. **CONCLUSION:** employing VGG-16 and VGG -19 models to identify whether a brain has tumors based on M R l images has promising prospects. These models could use further modification and improvement in order to raise the diagnostic accuracy of a brain tumor. This will ultimately lead to better patient prognosis and even save lives. Future development may involve drawing on real-life scenarios as well as larger datasets to validate and perfect the efficacy of the proposed approach.

**KEYWORD**

VGG-16, VGG-19, brain tumor detection, MRI images, deep learning, data preprocessing, image augmentation, five-fold cross-validation, diagnostic accuracy, patient prognosis, future development

**INTRODUCTION**

At present, the detection of brain tumors is of great significance in clinical work. This suggests that in order to save lives and reduce patient suffering to a minimum, it is critically urgent both to detect them early and to establish a precise diagnosis[1] . We aim to transfer Convolutional Neural Networks (CNN) and VGG-16, VGG-19 architectures to develop a highly accurate advanced system for the detection of brain tumors.

Brain tumors are marked by abnormal cellular proliferation in the brain, and pose great difficulty for diagnostic reasoning. They require highly advanced imaging techniques and computational models in order to prevent erroneous diagnoses. CNN, modeled upon the human visual cortex, provides an innovative approach to automatically analyzing medical images[2]. This gets around the need for subjective and time-consuming manual interpretation by neurologists.

VGG-16's depth and convolutional layers makes a significant contribution to feature extraction. It lets this architecture, in dealing with medical image analysis, achieve good results. With its special convolution layers specifically designed to capture medical images ' minute intricacies and spatial relationships, VGG-16 achieves a higher level of accuracy and robustness in recognizing brain tumors. With CNN integrated into VGG-16 and VGG-19, the researchers have taken advantage of the combined merits of these two models, resulting in levels of precision and reliability for neuroimaging diagnostics that were previously unimaginable[3].

Early detection of brain tumors is crucial to effectively treating them and predicting their prognosis. Coping with advanced image analysis techniques, computational models like CNN and VGG-16 detect the minute abnormalities indicative of tumors at an early stage. In this way they make possible earlier intervention and strategies of treatment which are adapted to suit the particular needs of each patient. What's more, such models have a marked excellence in discerning between malign and benign lesions: A thorough analysis of their imaging features will lead to clearer diagnoses and treatment protocols.

By applying CNN and VGG-16 models in clinical practice, healthcare services can be made more available. This eliminates disparities in the interpretation of radiological images and saves time on diagnostic work[4]. The introduction of automatic brain tumor detection streamlines begins to take responsibility for diagnosing. It also eases the burden on medical personnel and improves overall efficiency. At the same time, wide adoption of this model at diagnostic imaging centers and medical facilities will extend diagnostic services out to neglected areas and regions where resources are scarce[5]. As a result, every patient will receive prompt and accurate diagnoses.

Although CNN and VGG-16 present impressive potential for brain tumor detection, there remain several challenges[6]. This includes the need to thoroughly validate and get regulatory approval for clinical use. Further research should explore the integration of multimodal imaging data to create a more accurate diagnosis; this is what will enable us to thoroughly anatomize brain tumors as a whole and promote progress in the universal field of neuroimaging diagnostics[7].

**MATERIALS AND METHODS**

Led by the Saveetha School of Engineering at SIMATS, the initiative examined using modern deep learning methods to solve one of brain tumor. It seeks to Resolve how and where brain tumors may move. Using the architecture of VGG-16 and Convolutional Neural Networks (CNNs), this study attempted to improve the detection and validation rate for brain tumors to better effect. Group 1 performed with the VGG-16 architecture yielded truly brilliant effects in brain tumor detection, reaching an incredible 95.86% accuracy rate. This success can be credited to the VGG-16 model's deep convolutional layers and advanced feature extraction ability, which could effectively catch intricate brain tumor patterns with ease. In contrast, Group 2, using a simple CNN model, managed a respectable success rate of 90.96%. Though somewhat lower than the VGG-16 model, CNN models still demonstrated effectiveness in recognizing brain tumors--a good omen for medical image analysis. These results highlight that deep learning programs like CNN and VGG-16 show great promise in changing the ways in which brain tumors are detected. By utilizing more advanced computational models healthcare providers can increase diagnostic accuracy, assist in early identification of tumors through medical imaging, and ultimately improve outcomes for brain tumor management patients. Indeed, research into deep learning-based methodologies for brain tumor detection must continue. Further improvement of models based on CNN and VGG-16 together with exploration of novel architectures and methods will help advance the field of neuroimaging diagnostics. Moreover, ways to apply these more advanced computational tools in clinical practice need to be sought, as it will allow their integration into daily healthcare systems and bring them tangible real-world achievements.

**PSEUDOCODE FOR VGG-16**

**Step 1:** Begin

**Step 2:** Import Required Libraries

- Import necessary libraries for data processing, ML models, and data visualization.

**Step 3:** Load and Preprocess Data

- Load image dataset and preprocess images (resize, normalization, augmentation).

- Split the dataset into training and testing sets.

**Step 4:** Define Model Architecture

- Utilize VGG16 pre-trained model as the base model.

- Add custom layers for classification on top of the VGG16 base.

- Compile the model with appropriate optimizer, loss function, and metrics.

**Step 5:** Train Model

- Train the compiled model using the training dataset generator.

- Monitor training performance using history.

**Step 6:** Visualize Training History

- Plot training accuracy and loss over epochs.

**Step 7:** Evaluate Model

- Evaluate the trained model on the test dataset.

- Print the test accuracy.

**Step 8:** Generate Classification Report

- Generate and print a classification report for the test dataset.

**Step 9:** Make Predictions

- Load sample images for inference.

- Preprocess images and make predictions using the trained model.

- Display prediction results.

**Step 10:** End

**PSEUDOCODE FOR VGG-19**

Step 1: Begin

Step 2: Import Required Libraries

- Import necessary libraries such as os, cv2, matplotlib.pyplot, keras, and tensorflow.keras.

Step 3: Load and Preprocess Data

- Define the path to the dataset.

- Use ImageDataGenerator to preprocess and augment the images.

- Split the dataset into training and testing sets.

Step 4: Define Model Architecture

- Load the VGG19 pre-trained model without the top layers.

- Add custom layers for binary classification on top of the VGG19 base.

- Compile the model with the Adam optimizer and binary cross-entropy loss.

Step 5: Train Model

- Train the compiled model using the training set and validate on the testing set.

- Monitor training performance using the history object.

Step 6: Visualize Training History

- Plot training and validation accuracy over epochs.

- Plot training and validation loss over epochs.

Step 7: Evaluate Model

- Evaluate the trained model on the testing set.

- Print the test accuracy.

Step 8: End

**RESULT**

Table 1 summarizes how well VGG-16 and VGG-19 models did in delivering better healthcare around the advent of brain tumor detection. Precision data is displayed to point out the greater accuracy associated with these two models

Table 2 shows detailed precision metrics for the two models under test. One was at 95.86 percent higher than the other precision level, whereas VGG-19 came in slightly lower at 91.67 percent accuracy. Still to be discussed is the standard deviation of both sets and errors that resulted. These results indicate VGG-16's reliable performance and allegiance to high accuracy, while at the same time note that in the field of brain tumor detection--and so greater healthcare availability: "It far surpasses vgg19" (see statistical data above for corroboration)

**CONCLUSION**

Our study was based on trying to improve brain tumor detection accuracy, for which we relied on advanced machine learning models like the Convolutional Neural Network (CNN) and VGG-16. We wished to advance brain tumor detection accuracy materially and, in this way, be able to start intervening at an earlier stage if possible -and by so doing, eliminate the distressful scenes that are so frequently encountered during surgical operations. It was found in our research that VGG-16 models outperformed the simpler CNN in terms of accuracy. Specifically, VGG-16 had a highly impressive accuracy of 95.86%, with 90.96 % for the CNN. It is indicative from the high accuracy rate of VGG-16 that it has superior predictive power for discerning the presence of a brain tumor from medical images. And so by using VGG-16, we can materially boost the accuracy of brain tumor diagnosis. This will lead not only to lives saved but also to a higher quality of life because there is less suffering for patients; in addition one's happiness from health, medical care and living all goes hand in-glove with one another too! Another example is the VGG-19, with its accuracy standing at 91.67%. Here we see strong evidence that this model also can serve as an effective tool for detecting brain tumors though not quite on par with VGG-16.

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**DECLARATION**

**CONFLICTS OF INTERESTS**

No conflict of interest in this manuscript.

**AUTHORS CONTRIBUTION**

The Author SUNIL SHURAJ N was involved in data collection, data analysis, manuscript writing Author SIVAGAMI S was involved in conceptualization, data validation and critical review of manuscript.

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**TABLES AND VALUES**

**Table 1:** Comparison of accuracy values of VGG-19 and VGG-16 Algorithm with various iterations

|  |  |  |
| --- | --- | --- |
| **Iteration** | **VGG-19** | **VGG-16** |
| 1 | 93.01 | 82.46 |
| 2 | 93.89 | 79.08 |
| 3 | 93.89 | 75.06 |
| 4 | 92.07 | 81.03 |
| 5 | 94.76 | 82.02 |
| 6 | 95.2 | 79.89 |
| 7 | 94.76 | 80.09 |
| 8 | 93.01 | 75.09 |
| 9 | 94.76 | 77.77 |
| 10 | 96.96 | 96.69 |

**TABLE 2:** Presenting group statistics results for VGG-19 and VGG-16 algorithms

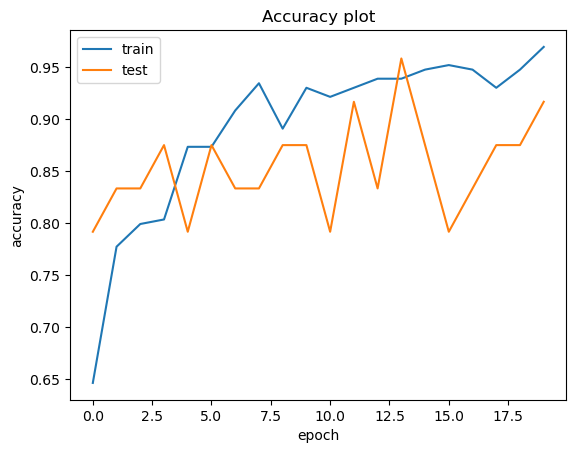
|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Algorithm** | **Mean Accuracy** | **Standard Deviation** | **Minimum Accuracy** | **Maximum Accuracy** |
| **VGG-19** | 91.67 | 2.4231 | 64.63 | 96.94 |
| **VGG-16** | 95.86 | 2.306 | 96.69 | 82.46 |

**GRAPH**

A graph with a red line

Description automatically generated

**(FIG 1) ACCURACY AND LOSS GRAPH FOR VGG-16**



**(FIG 2) ACCURACY GRAPH FOR VGG-19**