Integrating Hybrid Deep Learning Architectures for Accurate Brain Tumor Classification

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***Abstract*— An important part of medical imaging is classifying brain tumors since precise detection is critical to an early diagnosis and for the planning of effective treatment. This study presents a hybrid deep learning model combining two well-established architectures, VGG16 and InceptionV3, to classify brain MRI images into two classes : tumor and no tumor. The model combines the good of two complex convolutional neural networks (CNNs), taking the benefit of extracting features with VGG16 and spatial optimization with InceptionV3. The dataset of labeled brain MRI images is then used to train the hybrid model using transfer learning, fine tuning and regularization, and data augmentation is applied to the images to standardize their dimensions and normalize pixel values, as well as to increase the dataset size and decrease the risk of overfitting. Metrics such as precision, recall, F1-score, and overall accuracy are applied to evaluate its classification accuracy. The output highlights the model's ability to discriminate between tumor and non-tumor cases and demonstrates its potential for automated brain tumor detection. The goal of this research is to help radiologists to speed up and improve diagnostic accuracy to optimize patient prognoses in the overall management of brain tumors.**

INTRODUCTION:

A major health concern, brain tumors need to be detected timely and precisely so as to be treated properly.Most commonly, MRI scans are used to diagnose brain tumors, because they provide a detailed view of the brain's structure.ommonly used method for diagnosing brain tumors, providing images that are detailed view of the brain's structure. Manual analysis of MRI images is often time consume and prone to human mistakes. As a consequence, there has been a growing need for automated systems that assist radiologists in accurately detecting brain tumors. Deep learning, especially with Convolutional Neural Networks (CNNs), has witnessed some recent breakthroughs which show great promise in automating medical image analysis.

CNNs are a highly developed class of deep learning architectures designed to the most detail for image tasks with the classification. This is especially so for CNNs that are praised for their abilities to directly and accurately extract hierarchical features and elaborate patterns from raw pixel data, such as the tasks of image recognition. Each has convolutional, pooling and fully connected layers as well as other layers that work in conjunction to identify spatial hierarchies and complex local structures within images. This profound feature allows the CNNs to analyze all the features of an MRI scan that may be difficult for the human eyes to distinguish.

This research work presents a deep learning model that combines two strong CNN models, VGG16 and InceptionV3 to classify brain MRI images into tumor and no tumor classes. VGG16 is preferred because of its relatively simple network architecture and a large depth of the network's layers that feature detailed extraction of feature maps. On the other hand, InceptionV3 uses efficient architecture with multi-scale convolutional filters that allow network to detect different features within the images. Combining these architectures, the hybrid model incorporates the considerable advantage of the former in order to potentially offer better classification accuracy.

The hybrid model is derived from a large database of brain MRI images with the help of transfer learning and fine tuning. To avoid such a situation, techniques like data augmentation and those belonging to the broad group of measures against overfitting are used. The proposed strategy enhances the model's ability to classify between tumor and non-tumor cases; therefore, such hybrid CNN models hold promise for enhancing medical image analysis. The purpose of this work is to create a dependable and effective method for diagnosing brain tumours, which will help doctors make faster and more accurate results in patients' treatment.

1. LITERATURE SURVEY:

In the last decade, deep learning and machine learning approaches have been considered revolutionary in medical imaging especially in detection and diagnosis of glioma.

[1] The convolutional neural network (CNN) was developed by Huang et al. (2023) for use in MRI images with the aid of complex network principles. Consequently, there is a classification of brain tumors. Their model is equipped with a differently trained activation function to increase the efficiency, an example of complex network-inspired architecture in medical image analysis, [2] Almufareh et al. (2024) proposed an automated system for to segment and classify brain tumor using deep learning model named YOLO.

Multiclass classification of malignant brain tumours using sophisticated algorithms in machine learning were advanced by Vidyarthi et al. (2022) [3], and the authors focused on the application of advanced techniques in the differentiation of various types of tumours, thus underlining the need for advanced techniques in the enhancement of classification. In the same way, Khan et al. (2024) proposed a dual-approach model that involves the transformer semantic segmentation with a triplet preprocessing technique for early Alzheimer's diagnosis. [4].

Agarwal et al. (2023) present a multi-DL model approach for the detection of brain tumor in MRI scans to improve the accuracy and reliability in classification [5]. In another study, Kumar et al. (2024) work on breast cancer detection through mammogram analysis and show that deep learning models can be applied to a variety of medical imaging classification problems, which can be insightful for similar problems in a different field.

The authors Majib et al. (2023) propose a novel deep learning architecture known as VGG-SCNet based on the VGG architecture for the detection of brain tumors. Their work provides more understanding on the performance of VGG networks, particularly in the analysis of MRI images, thereby contributing to the growing work done on DL based tumor detection [7]. Along the same line, Jia et al. (2024) propose a method for the detection and diagnosis of brain tumors based on deep learning and support vector machine classifiers to classify MRI images of various tumor classes [8].

Mohsen et al. (2023) for brain tumor classification employ a combined approach with ResNext101_32×8d and VGG19 pre-trained models along with single image super-resolution. In their paper they explain how using several pre-trained models in parallel can improve results in medical image classification.[9]

Last, but not the least, SenthilPandi et al. (2023) discuss tumor segmentation and volumetry using an adaptive multiple resolution contour model. Although they have adopted it to lung tumors, their work provides important general information on tumor segmentation methods that can be useful for brain tumors as well .[10]

Altogether, these works stress the various types of deep learning techniques used in the classification and segmentation of brain tumours and the value of CNNs, YOLO, and transforms in the improvement of medical image analysis.

2. METHODOLOGY:

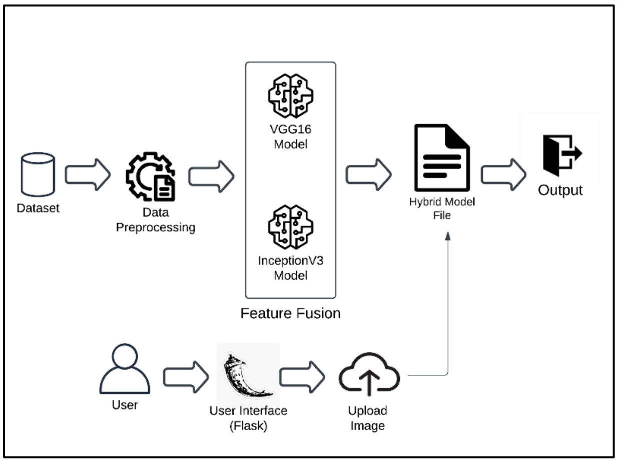

Figure 3.1 Architecture Diagram

The system that is proposed in this paper uses a new concept of a dual-model deep learning model that incorporates the VGG16 and InceptionV3 neural networks. The beginning involves the acquisition of raw data, which is preconditioned through a number of intermediate steps that help to manipulate its input for better feature presentation. This refined dataset is used in the feature fusion phase whereby the two neural networks run in parallel to extract some features from the processed data. The more advanced in feature hierarchy selection VGG16 is implemented together with the InceptionV3 that is also powerful in multi-scale feature extraction. This parallel processing approach leads to a highly advanced dual structural plan that makes the best use of the two architectures. This has been made possible by the development of a Flask based web interface through which the various user interactions with the model can be performed without any problems. By using this interface, users can upload images which are then followed by the hybrid model to provide results.

a. Structure of the dataset:

The dataset utilized in this project consists of MRI brain images classified into two primary categories: Tumor and No Tumor. The 'Tumor' group consists of MRI scans of patients with different types of brain tumors , while the 'No Tumor' group is comprised of scans from patients with no brain tumors .All images are in standard formats that include '.jpg' and all images are resided to 150 * 150 pixels to be compatible with the model.

The data set is split consistently into training and validation data where 80% is used for training and 20% for validating the data while in the development process. This structured approach of handling the data guarantees that all the data is properly utilized and the creation of a sound model to identify the tumors as accurate as possible.

Sample dataset :

Name	Type
Testing	File folder
Training	File folder

Figure 3.2

Folders with images for train and test the model

Name	Type
No Tumor	File folder
Tumor	File folder

Figure 3.3

Each folder consists of two classes

No tumor and Tumor

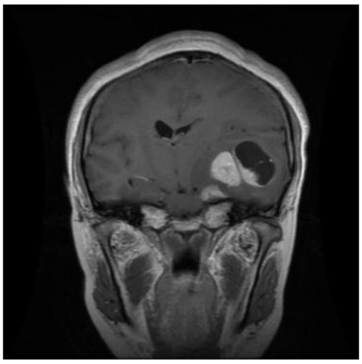

Figure 3.4

Sampe Image of Dataset

b. Preprocessing Data:

Preprocessing is important in the process of making the images ready for training, and enhance the model's performance. Inclusion of data quality and diversity involves flipping of images, rotation, and changes in brightness.

Image flipping: In one of them, it requires the images to be mirrored horizontally or vertically in order to help the model to learn any patterns regardless of the orientation of the images. For instance, flipping can also mimic actual variations where a tumor may appear on either side of an image.

Rotating images: Another important augmentation technique, where the images are rotated at arbitrary orientations. This makes the model insensitive to the orientation and hence makes the model more resistant to this aspect.

Changing brightness: It controls the brightness of the image as it changes to replicate actual lighting in one's day to day life. It is possible to make the brightness slightly higher or lower and the model will be able to recognize features stably while the lighting conditions are different.

These preprocessing techniques make the dataset more diverse, and avoid overtraining the model in the process of classification.

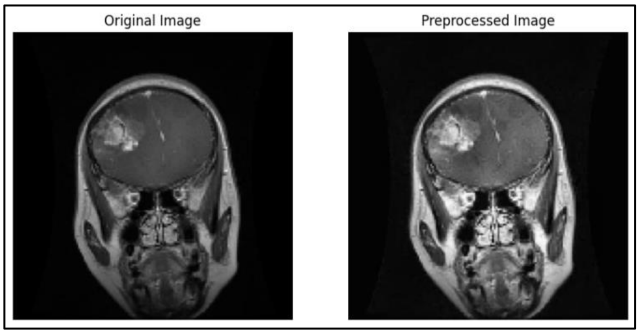

Figure 3.5

Original Image Vs Preprocessed Image

c. Featrue Extraction:

Feature extraction is an important stage where deep learning models are used in order to extract significant patterns from input images themselves. In this methodology, two highly efficient pre-trained convolutional neural networks VGG16 and InceptionV3 have been used. VGG16 has detailed structure and executes distinct architecture, docketing a deep stack of convolution layers with small 3 x 3 filters providing hierarchical features like edges and textures.

Unlike InceptionV3 which contains Inception modules analyzing the input data at different scales at the same time. This capability makes it easy for InceptionV3 to identify different and complicated characteristics within an image. The two models are initialized on the ImageNet which provides them a basis for general image features detection. In this case, their classification layers are stripped off leaving only the feature extraction layers for this task.

This shift guarantees that the models do not make predictions during feature extraction of images but only learns representations. We then combine the feature maps of the two former models, VGG16 and InceptionV3 as they complement each other. The merging turns out to produce a more complex feature space than the one in which the input images lie, as VGG16 offers spatial features while InceptionV3 offers multiple scale features.

These feature maps are fused together to get the hierarchy map, which characterizes the features from two models at different times. The fact is that when merging VGG16 with InceptionV3 multi-scale analysis, the hybrid model is made significantly more effective in classification of the tumor images from non-tumor ones, which consequently results in the increase of the classification accuracy.

d. Development of User Interfaces:

The user interface is developed using Flask, a Python-based web application framework for creating business-oriented applications to classify users' inputs. Flask is also quite lightweight and can be easily deployed for creating machine learning applications. It provides users with an ability to upload medical images through the Web page interface and the interface is designed as a simple Web page.

When a user uploads an image, then Flask takes the image and processes it through the same steps as in the training process including scaling and normalization. The preprocessed image is then fed to the hybrid model and from which a prediction is made. This result showing whether the image has a tumor or not, is presented on the web page for the user.

The Flask-based interface guarantees openness, which means that the healthcare professionals can easily implement the features of the model without any programming experience. Moreover, the interface is designed to be scalable for future updates, or for introducing other new features.

4. RESULT AND DISCUSSION:

The Figure 4.1 summarizes the results of the evaluation of the classification model for the "No Tumor" and "Tumor" classes.The "Precision" measure, which reflects the probability of true positive predictions for each class, comprises 0.75 for "No Tumor" and 0.90 for "Tumor," which means that the "Tumor" class is recognized more confidently. The "Recall," or the proportion of actual positives correctly identified is 0.85 for "No Tumor" and 0.82 for "Tumor" which means there is better sensitivity towards the "No Tumor" class. The overall performance for each of the classes is given by the "F1-score," a parameter that is the harmonic mean of precision and recall; it is equal to 0.80 for "No Tumor" and 0.86 for "Tumor."

The number of actual samples of each class is described in the "Support" metric; there are 405 samples with "No Tumor" and 906 – with "Tumor." The model has an 0.83 accuracy, which is an overall of 1,311 total instances, and the model is right in 83% of the cases. These results again confirm the overall applicability of the model but also indicate the points that might still be worked on, such as increasing the precision and recall of the "No Tumor" class for higher overall accuracy.

	Precision	Recall	F1-score	Support
No Tumor	0.75	0.85	0.80	405
Tumor	0.90	0.82	0.86	906
Accuracy			0.83	1311

Figure 4.1 Performance Metrics

The Figure 4.2 provides a visual summary of the classification model's performance in identifying two categories: "No Tumor" and "Tumor." The format of confusion matrix is used where rows are Actual classes (True classes) and columns are Predicted classes made by the model.

The first cell in the table's top left corner also presents true negatives 344, which are cases correctly classified as 'No Tumor.' The true positives are in the bottom-right cell, which are 742 and we can see that the cases in the "Tumor" group were correctly recognized.

The cell 82 in the top-right quadrant represent the false positives where the model has classified instances as "Tumor" where there is "No Tumor". Likewise, the cell in the bottom left corner (61) represents the false negatives, where the model misclassified samples as "No Tumor" while they are actually "Tumor".

The color gradient used in the matrix provides an intuitive understanding of the count distribution, with darker shades representing higher counts and lighter shades denoting lower counts. This visual format emphasizes The model's ability to accurately classify most of the instances while drawing attention to areas where misclassifications occurred.

The high accuracy of the model is clearly seen in the high number of true positive and true negative in comparison with the false positive and false negative. However, there are always random errors that lead to misclassifications hence the need for fine-tuning the model for micro accuracy and micro recall of the two classes may be by handling problems such as class imbalance or setting better decision margins.

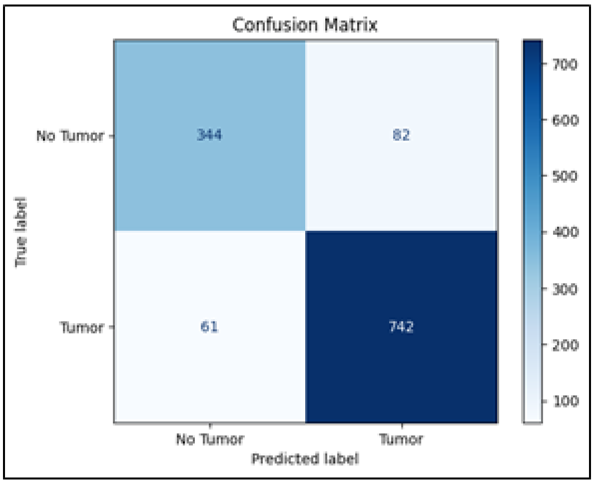

Figure 4.2 Confusion Matrix Diagram

This Figure 4.3 shows how a brain tumor classification model performs by showing the sample MRI scans and correctly and wrongly classified images. The grid is divided into four sections to illustrate four possible scenarios of actual and predicted labels. The first image in the top left is an MRI with true label, Tumor, and the model has predicted it to be Tumor, which is correct so it falls into the True Positive category. This suggests that the model possesses the ability to localize the tumor-affected areas in the MRI scan correctly. The last image in the top-right corner is the scan identified as “No Tumor” and the model also predicts this as “No Tumor” (TN); thus, it can also identify non-cancerous cases rightly.

The misclassification could be as a result of some tumor characteristics being less conspicuous or not as clearly defined as in the other cases. It is such errors that may cause dangerous conditions on tracks and roads to be missed out on.

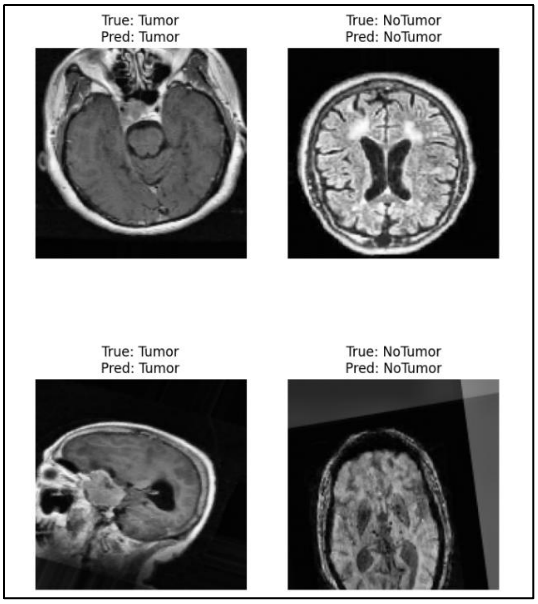

Figure 4.2 True Vs Prediction Diagram

These mistakes may be caused by noise in the image or by formations that look like tumors to the model and lead to an incorrect conclusion. Through these examples, the image also makes the viewers pay attention to the model’s weakness of false negative and false positive results which could be improved by the more complex model structure, better dataset, or more effective preprocessing methods. The results show that the proposed model has reasonable success in correctly categorizing MRI scans into the “Tumor” and “No Tumor” classes with an overall accuracy of 83%. Although the model provides feasible accuracy with higher precision on “Tumor” cases and higher recall on ”No Tumor” instances, the assessment reveals some of the aspects to improve. False negative and false positive cases indicate possible difficulties in identifying specific characteristics of the tumor or distinguishing between normal and neoplastic tissue patterns. The confusion matrix and sample MRI classifications show that the model needs further enhancement in handling of imbalanced classes as well as in enhancing its predictive accuracy.

5. CONCLUSION:

Overall, the proposed brain tumor classification model achieves an overall accuracy of 83% when differentiating between “Tumor” and “No Tumor” using MRI scans. The accuracy, recall, and F1-score assessment indicators characterize the model for making accurate predictions, and more specifically, for the identification of tumor cases. That being said, it is possible to mention some of the directions for the further work: an increase in the accuracy of classification (both true positives and true negatives) is the biggest concern that can limit the model’s applicability.

Based on the confusion matrix and sample predictions, the model’s performance is revealed, and specific issues in identifying small tumors and discriminating between normal and abnormal tissues are identified. Hence, these results indicate the directions for the improvement of the model, namely, the quality of the dataset, the problem of unbalanced classes, and the architecture of the model. In conclusion, the project supports a strong base for automated identification of brain tumors and can serve as an aid to the personnel in order to arrive at an early diagnosis.

6. FUTURE WORK:

The current hybrid model for brain tumor classification has revealed potential in the discrimination between the tumor and non-tumor categories. But, it is necessary to develop it further to incorporate wider diagnostic capacity and improve its ability to distinguish between different tumours, such as gliomas, meningiomas or pituitary tumours. This would entail fine tuning the model to look for differences in tumor morphology and texture, which is not easy because of the nature of medical imaging.

Also, a clean and easily navigable website, where the radiologists would be able to upload MRI scans, view results, and interpret the tumor classifications would enable easy adoption into clinical practice. Maintaining model accuracy and usability can thus assist the healthcare professionals in making quicker, better decisions which can in turn support clinical decision making. Future work should involve improving the presented model and making it more relevant to real practice for clinicians.

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