INTEGRATING HYBRID DEEP LEARNING ARCHITECTURES FOR ACCURATE BRAIN TUMOR CLASSIFICATION

PHASE I REPORT

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BONAFIDE CERTIFICATE

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ABSTRACT

Medical imaging classifies brain tumors and is essential in early detection and the development of an effective treatment strategy.. This analysis introduces a hybrid deep learning model that integrates two robust architectures, VGG16 and InceptionV3, to classify brain MRI scans into two categories: tumor and no tumor. The hybrid approach combines the feature extraction power of VGG16 and spatial efficiency of InceptionV3 to get an all around analysis of the input pictures. Image resizing, normalization, data augmentation and similar preprocessing steps are applied to improve dataset quality, to address data scarcity, and to reduce overfitting. We use transfer learning and fine tuning techniques to make use of pre trained weights and speed up convergence and improve performance. It includes regularisation method to decrease the model over fitting and improve generalization. Model is trained and evaluated on a labeled dataset of brain MRI pictures. Experimental results of the model's performance are evaluated using accuracy, precision, recall and F1-score, and prove that the model is able to distinguish between tumor and non tumor pictures with high accuracy and robust predictive capabilities. The hybrid model provides a useful tool for automating brain tumor detection, reducing radiologists' workload and supporting clinical decision making. We propose an approach that can help to ensure reliable and timely diagnosis and in turn help improve patient outcomes and advance the use of AI in healthcare applications.

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LIST OF ABBREVIATIONS

S. No	ABBR	EXPANSION
1	Adam	Adaptive Moment Estimation
2`	AI	Artificial Intelligence
3	API	Application Programming Interface
4	BCE	Binary Cross-Entropy
5	CNN	Convolutional Neural Network
6	DFD	Data Flow Diagram
7	DSS	Digital Signature Scheme
8	DL	Deep Learning
9	HTTP	Hypertext Transfer Protocol
10	JPEG	Joint Photographic Experts Group
11	KNN	K-Nearest Neighbors
12	ML	Machine Learning
13	MRI	Magnetic Resonance Imaging
14	NN	Neural Network
15	PIL	Python Imaging Library
16	ResNet	Residual Network
17	SVM	Support Vector Machine
18	UI	User Interface
19	VGG	Visual Geometry Group
20	YOLO	You Only Look Once

CHAPTER 1

INTRODUCTION

1.1 GENERAL

Of all the diseases, brain tumors are among the most dangerous, with the correct and timely diagnosis being critical to treatment. MRI is a significant instrument in the medical area to show the distinct structures and the anomalies of the brain. However, MRI scans interpretation is a complex process that demands a lot of effort and time and expertise. To overcome such complications, automated brain tumor classification system with the help of artificial intelligence (AI) has gained much attention in the recent past.

One of the interpretations of AI, namely, deep learning, has scored truly impressive results in solving image classification problems without involving any interaction with the raw data. CNNs are especially useful in medical imaging, because the network is able to find patterns in pictures, which are not visible to the human eye. However, problems like data deficiency and overfitting are still persistent in medical image analysis, and therefore, new ideas should be developed to enhance model's precision and dependability.

This project proposes a hybrid deep learning model that combines VGG16 and InceptionV3, two widely used CNN architectures, to classify brain MRI scans into two categories: tumor and no tumor.

The features extraction capabilities of VGG16 and the spatial characteristics of InceptionV3 are combined, in this proposed model, to improve classification accuracy. Preprocessing such as image resizing is used to solve such fluctuations with data augmentation. The work aims to provide a system for radiologists to aid in the detection of brain tumors with high accuracy and in a timely manner. Through this study, the authors hope to minimize diagnostic errors by automating classification in the management of brain tumors with an overall view of enhancing patient care.

1.2 OBJECTIVE

The primary objective of this project is to develop a robust and efficient hybrid deep learning model for the classification of brain MRI pictures into two categories: tumor and no tumor. Based on the features of the VGG16 and InceptionV3 models, the model will achieve high accuracy of brain tumor detection, overcome the problems of data deficiency and overfitting. The work entails concentration on the methods of preprocessing the data, and tuning to improve the model. Finally, it is desirable to develop a highly competent device that will assist radiologists in making direct and timely diagnoses in order to increase the chances of a positive outcome for the patient. The goal of this approach is to fill the gap between the automation of diagnostics and clinical experience, improving the reliability and speed of medical decision making.

1.3 EXISTING SYSTEM

Current approaches on classification of brain tumor are based on the conventional machine learning algorithms or isolated deep learning structures like CNNs. Even though these approaches have been applied and have demonstrated promising results, they suffer from certain drawbacks including inadequate accuracy, great reliance on large annotated datasets, and overfitting. The conventional methods entail applying feature extraction through manual choice, which is slow and not efficient for the large medical imaging data. Despite the effectiveness of single-model CNNs, the networks may fail to learn the fine-grained dependencies of brain MRI pictures. These challenges presuppose the development of more complex hybrid architectures that incorporate several architectures to enhance the efficacy and precision in the detection of brain tumours.

1.4 PROPOSED SYSTEM

The proposed system is a hybrid deep learning architecture that combines the strengths of VGG16 and InceptionV3 for brain tumor detection in MRI scans. This model provides a full blown analysis of brain images balanced with VGG16 feature extraction and spatial efficiency of InceptionV3. Training time is accelerated and model performance improved by using transfer learning. This combination of the approach with inexpensive, widely available microscopes enables quicker, more precise tumor detection, thereby enabling clinical decision making and streamlining health care workflow.

CHAPTER 2

LITERATURE SURVEY

In [1] Huang et al., (2024) propose a new method to classify brain tumor using CNNs along with features from complex networks. In segmentation of brain MRI scans, they propose a new activation function that they believe improves the convergence and effectiveness of basic CNNs. As a result, the authors can use complex networks to model relationships between MRI image features that may be difficult for conventional CNNs to discover. Their method, which shows better classification performance than standard CNN based approach for medical imaging tasks, is particularly evident.

In [2] Almufareh et al., put a lot of emphasis on segmentation and tumor classification in the brain using a YOLO based deep learning approach, it would be interesting to explore another approach to this problem. YOLO as a real time object detection system is used to segment the tumors in the brain. They are an application which is very accurate and efficient, and hence they improve their system to serve the medical image analysis system better. YOLO is able to bound the segmentation area of tumors. So this is an extension of classification results in the shortest time possible. Deep learning features are automatically extracted and with a physician and other experts, further reduction of the physician and other expert roles in the diagnostic process is achieved. The result indicates a high segmentation accuracy on tumor classification of the proposed method.

In [3] Vidyarthi et al., (2022) propose a method for classifying multiple class glioma. First, they extract the features of different characteristics from the MRI pictures through feature extraction and then they use the classifiers for the classification of different types of brain tumors. For tumor diagnosis, the problem of multiple classes is more difficult than binary classification, the authors say. The authors improve the classification performance by employing machine learning algorithms, features selection and a new approach to classification. The second focus of the paper is on the importance of correct classification of different tumor classes with implications in treatment and patient management.

In [4] Khan et al., (2024), the authors introduce the innovative method of early Alzheimer’s disease detection, Dual-3DM3-AD, which uses mixed transformer based semantic segmentation and triplet pre-processing. The principles described in this study are generalizable to brain tumor detection, although they are specific to Alzheimer’s disease. In order to achieve this, the authors use a transformer network to segment and classify MRI pictures for early detection. Preprocessing triplet helps the learning process because it magnifies the feature extraction of the system and makes the model more robust to noise. These methods have good performance in the preliminary identification of neurological disorders, and the integration of improved segmentation and preprocessing methods is not explored in this paper, but it may be a way to improve brain tumor identification systems, particularly in the face of complex medical pictures.

In [5] Agarwal et al., (2024) recently propose a combined system for brain tumor identification from MRI pictures. To improve the tumor detection of the brain, their model merges features from deep learning feature extraction and traditional image processing. In conjunction, the hybrid system outperforms both systems due to more accurate detection and classification. The authors go on to explain some of the benefits of this combination, for example, it allows peeling back some details of the tumor that may not be visible using one of the methods. In addition, the model reduces the probability of overfitting and so increases the capacity to generalize when using unseen data. Based on their findings, they can prove that their hybrid system is more efficient than conventional approach, therefore, the hybrid system is a feasible solution for the automatic detection of tumors in brain.

In [6], Kumar et al., propose a deep learning method to diagnose breast cancer from mammogram pictures based on deep neural network and image processing methodology. The concept can be generalized to brain tumor detection using CNNs in medical image analysis as this study has been done for breast cancer detection. The importance of feature extraction and model retraining is directly related to the classifying of tumors from brain MRI pictures and that is the reason why authors pay much attention to that. Augumentation of Data are applied to address the problem of a small number of medical samples that is crucial for improving the reliability and effectiveness of the tumor classification systems.

In [7] Majib et al., (2024) develop the VGG-SCNet framework for tumor detection in the brain using deep learning based on VGGNet. Using VGG16, a pre trained CNN, they extract features from MRI scans and classify the images as tumor or non tumor. Moreover, the authors employ a spatial context network (SCNet) in the model to circumvent the restriction of standard CNNs and learn spatial context from the images. This thesis proposes a system for analyzing brain MRI scans, which is able to achieve high accuracy and efficiency in tumor detection given the complexity and variability in such scans. We show that the integration of VGGNet and SCNet dramatically improves the classification of brain tumors, and the model's ability to interpret various MRI data. The hybrid approach improves tumor detection reliability and precision, leading to better clinical decision making and faster diagnosis.

In [8], Jia et al., used a deep learning approach to diagnose and classify tumors in the brain in MRI pictures . They use several deep learning models: We use CNNs and fully connected networks to classify pictures with respect to tumor presence and type. The authors then elaborate on a number of optimization techniques which can be used to improve these models such as learning rate optimization and activation functions. Therefore, their work is concerned with the problems associated with the use of medical image datasets, in which pictures can be very different in quality and large amounts of labeled data are required. The authors demonstrate that deep learning can improve diagnostic results when deep learning pipelines are well optimized for the classification of brain tumors

In [9], Mohsen et al., (2024) present a hybrid technique that combines single image super resolution with deep learning models to enhance classification of tumor in brain in MRI pictures. When dealing with low resolution medical pictures, the authors use super resolution to enhance the quality of input pictures. This improvement makes deep learning model effectively extract more accurate feature from MRI scans and raises the classification performance. Their results show that the hybrid approach outperforms standard classification models, demonstrating the potential of combining image enhancement techniques with advanced CNN architectures for more accurate and reliable brain tumor detection.

In [10] SenthilPandi et al., (2023) develop an adaptive multiple resolution contour model for lung tumor volumetric estimation and segmentation. We aim to segment lung tumors, but the proposed model's concepts can be extended to the segmentation of brain tumors. The adaptive contour model was designed to be robust for pictures of different resolutions, and therefore to help segment tumors and estimate their volume. This allows the authors to get more accurate segmentation, which is especially important when estimating the size of the tumor and creating a treatment strategy. This work details a new approach to increasing tumor detection accuracy and can be applied to other types of medical imaging, such as the MRI of the brain scan. Additionally, the multi resolution approach is robust to a wide range of imaging conditions. As a result, it is a flexible solution for problems with complex diagnostics in many medical applications.

In [11] Kumar et al., (2024) have put forward a CNN based model for MRI image based brain tumor detection. Their approach involves using more than one CNN architecture to take advantage of the efficiency of each architecture. The authors use the VGG16 model for feature extraction and then use their own CNN model to refine the features for tumor classification. In this work, the authors combine these two models to enhance accuracy and speed of the tumor detection system for brain. They also demonstrate that proposed hybrid model has better performance compared with single CNN architectures in terms of time and precision. This approach shows that different structures of neural networks can be integrated to improve the identification of brain tumours.

In [12] Verma et al., (2024) also investigate deep learning approaches to detect tumor in brain with MRI pictures while focusing on the model architecture to enhance the performance of deep learning. They also use a CNN based architecture that incumbents some capabilities in order to avoid overfitting and also to improve generalizing the tumors in brain. To address the lack of labeled data in medical imaging datasets, the authors describe data augmentation as a means of addressing this problem. By training and testing the proposed deep learning framework on a dataset and using cross-validation, the results showed good classification accuracy, especially in distinguishing tumors that are difficult to diagnose. This research shows deep learning techniques that are tailored to the characteristics of the medical image data set especially in the diagnosis of early brain tumors.

In [13] In Liu et al., (2024) propose a combination of Convolutional Neural Networks (CNNs) and Long Short Term Memory (LSTM) networks is proposed for a multi class brain tumor classification system. To extract spatial features from MRI images, CNNs are applied to learn, and LSTMs are introduced to learn temporal features to analyze sequential information in MRI slices. The fusion approach improves the model's ability to improve prognosis across different brain tumor types by integrating both spatial and temporal data. Using this model to classify three different types of tumors, the authors show high accuracy. In addition, this method provides important information for optimizing tumor characterization and personalized treatment strategies, and it is an indispensable tool in clinical medicine for the advancement of diagnostic capabilities.

In [14] Yadav et al., present an advanced deep learning model for the classification of brain tumors using MRI that embeds hybrid methods. The authors approach combines CNN with SVM to build a composite classification model. An SVM classifier is used to further improve the classification results with CNNs applied first for feature extraction. The authors argue that the combination of CNN and SVM improves general classification performance and tumor classification between benign and malignant. The study shows that the use of deep learning networks is more accurate than the use of CNNs alone, which can be a means to improve automated systems for brain tumor detection. In addition, this hybrid approach reduces the amount of false negatives which is important for medical diagnosis.

In [15], Zhang et al., (2024) consider the effectiveness of two sophisticated deep learning structures, ResNet and DenseNet, for the detection and categorization of brain tumors. The authors give insights into what ResNet's residual connections solve vanishing gradient issue and what DenseNet's dense connections improve feature reuse. These models are very effective in extracting complex patterns in the MRI scans of the brain. The authors also combine the two models in parallel to yield a high classification performance of brain tumours. We show that more complex CNN structures (e.g. ResNet and DenseNet) can improve the effectiveness of brain tumor detection by allowing radiologists to diagnose timely and accurately.

In [16], Patel et al., (2024) applied VGG16, ResNet and InceptionV3 for deep transfer learning to enhance the classification of brain tumors. To address the problem of limited training samples in medical imaging, transfer learning is leveraged to adapt models trained on large scale datasets for medical image tasks. The authors show that the pre trained networks are very accurate in classifying brain tumors even when the dataset is small, and that transfer learning with the pre trained networks has a high accuracy. The convergence of this method is fast and suitable for clinical practice because it is hard to collect a large amount of labeled data. Our research shows that transfer learning has a big impact on medical image classification tasks and can help identify brain tumors. Additionally, it stresses how pre-trained models can be applied to domain specific medical datasets.

CHAPTER 3

SYSTEM DESIGN

3.1 GENERAL

3.1.1 SYSTEM FLOW DIAGRAM

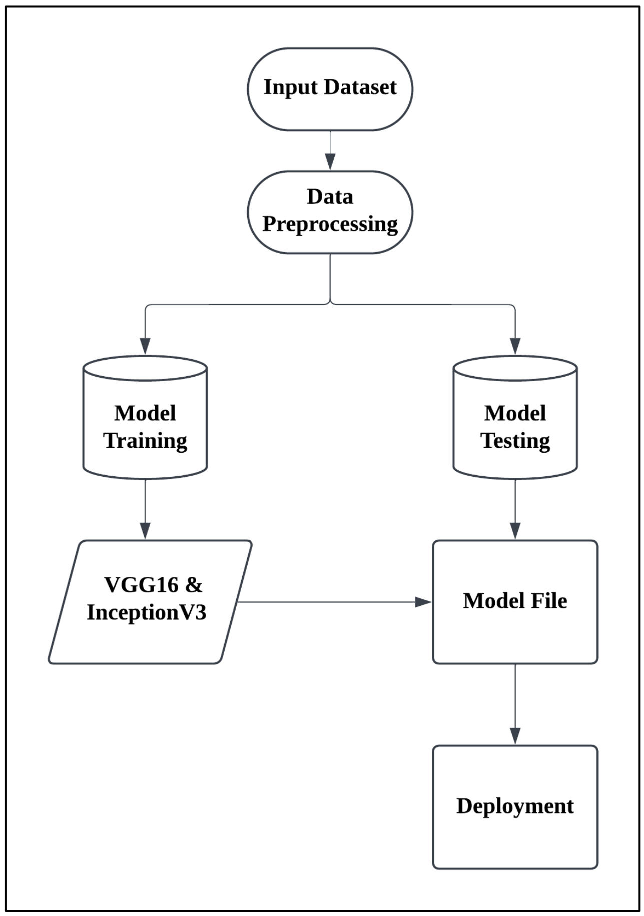

Figure 3.1: System Flow Diagram

The figure 3.1 shows the brain tumor detection system using a hybrid machine learning model workflow is shown in the diagram. We start with inputting a dataset of MRI images, and process them using data preprocessing steps like resizing, normalization and augmentation.

Then two deep learning models VGG16 and InceptionV3 are trained and tested with the preprocessed data. A hybrid model file is constructed by fusing the features obtained from both models. Finally, the model is deployed for use and is available for tumor detection tasks.

3.1.2 ARCHITECTURE DIAGRAM

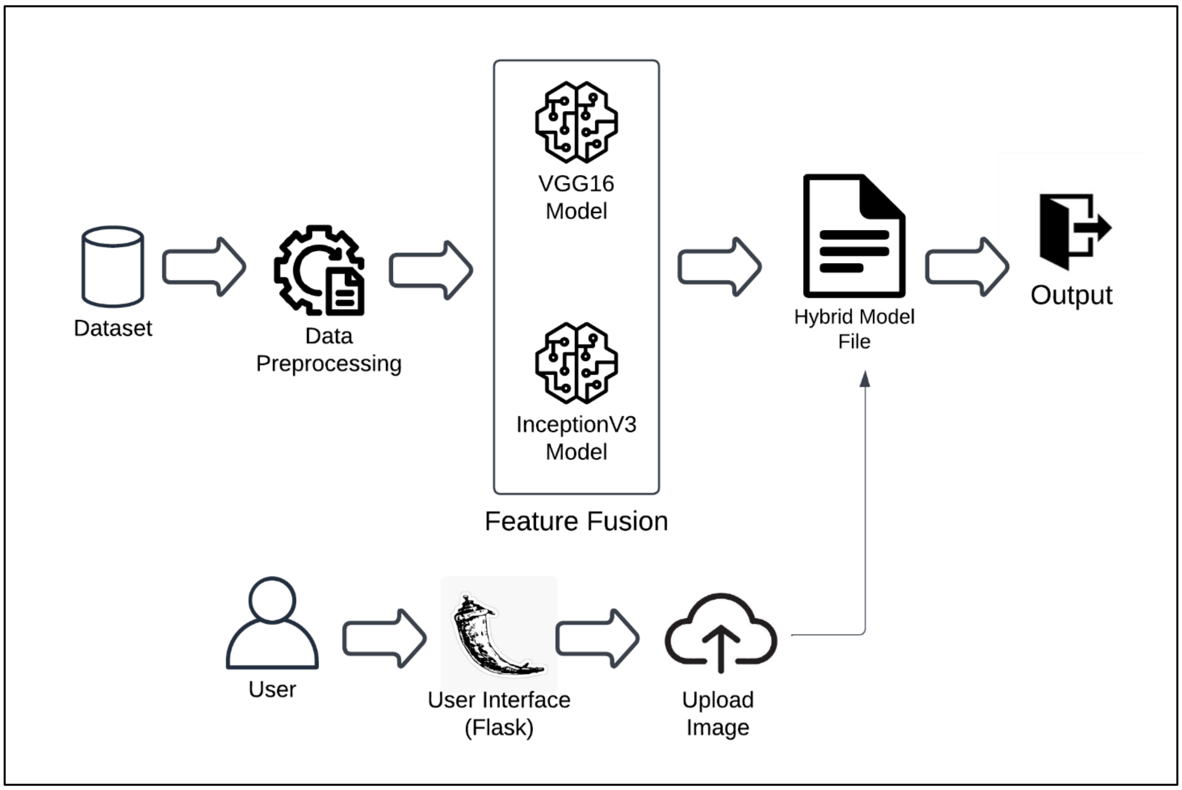

Figure 3.2: Architecture Diagram

The figure 3.2 gives the architecture of the brain tumor detection system using the hybrid machine learning model to process and classify MRI images efficiently. The input dataset for the system is a set of MRI images of the brain, which are preprocessed to resize, normalize, and augment the data so that the images are in good condition for model training.

The preprocessing techniques alleviate variations in image sizes, scale and contrast, making the dataset better and decreasing over fit.The data is then preprocessed, and passed through two deep learning models, VGG16 and InceptionV3, which are well known for their outstanding pattern recognition power. The MiraVGG16 is at a loss in understanding hierarchical image features while the Inceptionv3 catches the fine texture present in the images. These are independent models that feed their features online to a feature fusion technique that first fuses them to construct a richer and more robust representation.

We build a hybrid model by fusing the features, train it and save it for later use. A Flask based user interface is used in the system which makes it easy for healthcare professionals to upload MRI images for real time analysis. Once an image is uploaded, the hybrid model processes the image and classifies it into one of two categories: "tumor" or "no tumor." The user is shown this classification result to make quick and accurate medical decisions.

The system is developed to be continuously trained with new MRI images to improve accuracy and robustness with time. The architecture is also deployed across multiple platforms, making access to medical professionals and healthcare institutions easy. By automating the time consuming manual image analysis process, this deployment decreases the radiologist’s workload and enhances the overall speed of the diagnostic process.

3.1.3 USECASE DIAGRAM

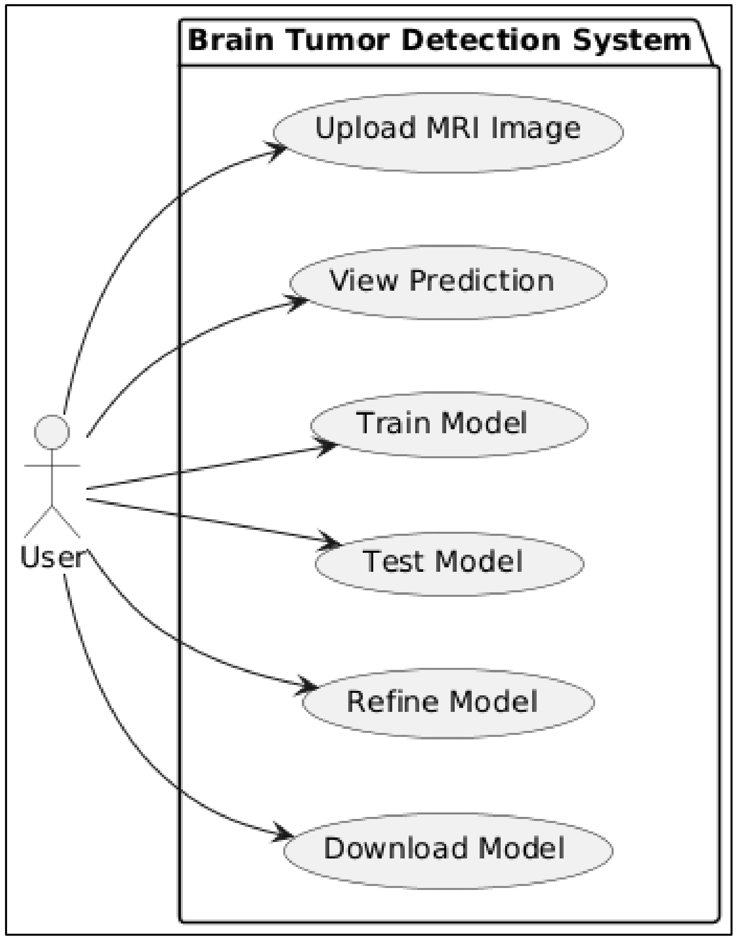

Figure 3.3: Usecase Diagram

This figure 3.3 gives the usecase digram for Brain Tumor Detection System represents the user interaction with the system. The system can accept MRI images uploaded by the user for analysis. Once you upload the image, you can see the prediction which classifies the image as "tumor" or "no tumor." The system also allows the user to train the model with new data, test the model’s performance and if necessary refine the model. Also the user can download the trained model. This demonstrates how the user can flexibly and control the system.

3.1.4 ACTIVITY DIAGRAM

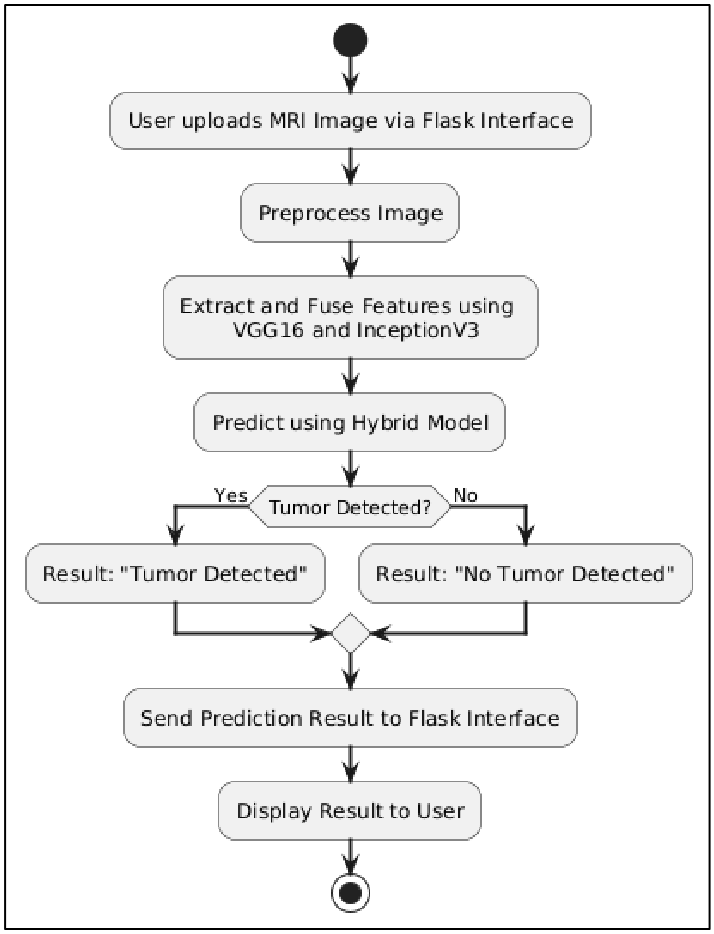

Figure 3.4: Activity Diagram

The figure 3.4 describes the activity diagram on how tumors are detected in MRI images. The user starts by uploading an MRI image. To increase quality and to ensure compatibility with the model, the image is processed. Two pre trained models, VGG16 and InceptionV3, are then used to extract and fuse features. A hybrid model is then used to predict whether a tumor is present or not. The system makes this prediction and it determines and labels the result as 'Tumor Detected' or 'No Tumor Detected.' Finally the Flask interface is sent the prediction result and displayed to the user.

3.1.5 CLASS DIAGRAM

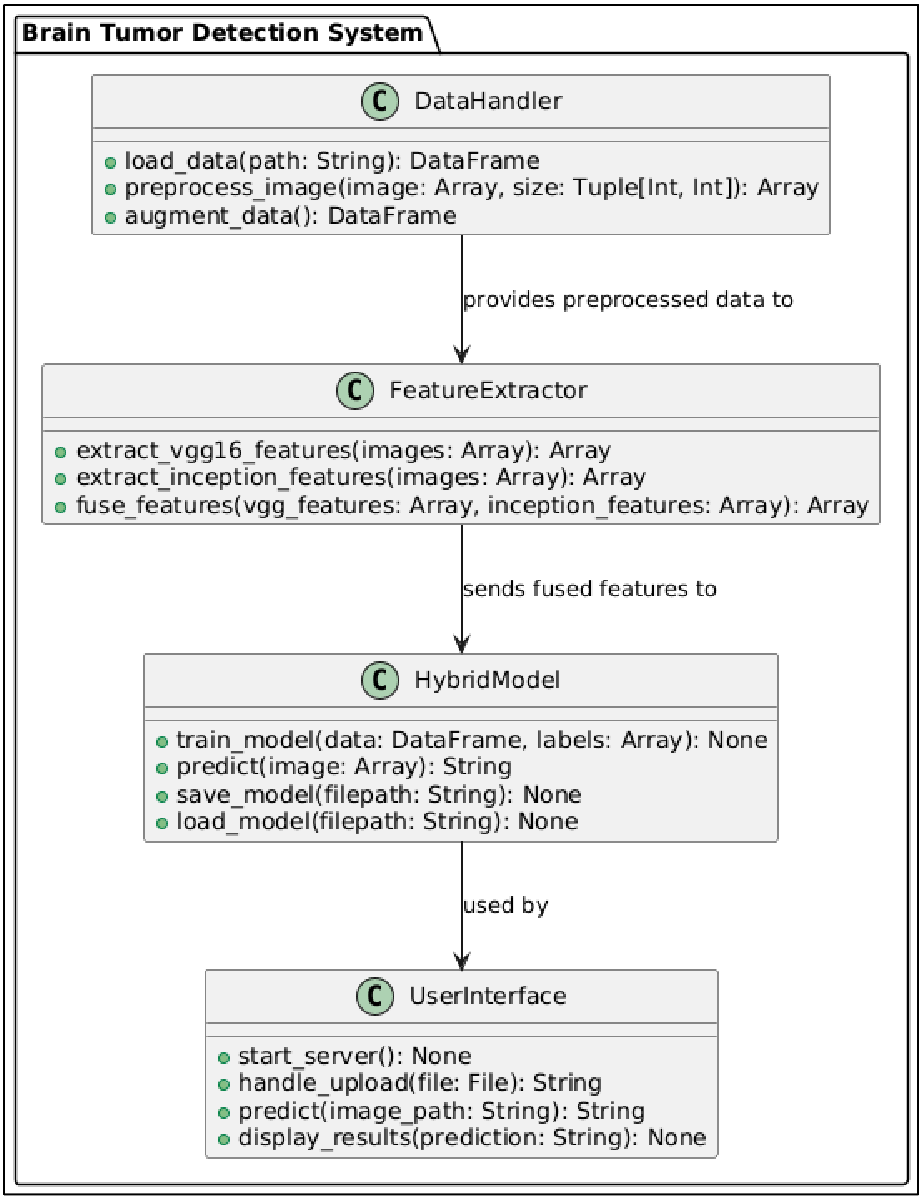

Figure 3.5: Class Diagram

The figure 3.5 gives the class diagram for this tumor in brain detection system. DataHandler class loads the data, preprocess the image and data augmented for further processing.

The FeatureExtractor class extract features from images using VGG16 and InceptionV3 models and combines them in a unified representation. They are then passed to the HybridModel class as a means to train and run a model, make predictions, and save or load trained models. UserInterface communicates with the system, performing server operations, uploading images, making predictions, and showing results to users. Preprocessed data is given to the FeatureExtractor which sends out fused features to the HybridModel using prediction or training. Then, the HybridModel is used by the UserInterface to predict tumor presence and show the results to the user. Each component is designed to take in a modular set of responsibilities within the detection pipeline.

3.1.6 SEQUENCE DIAGRAM

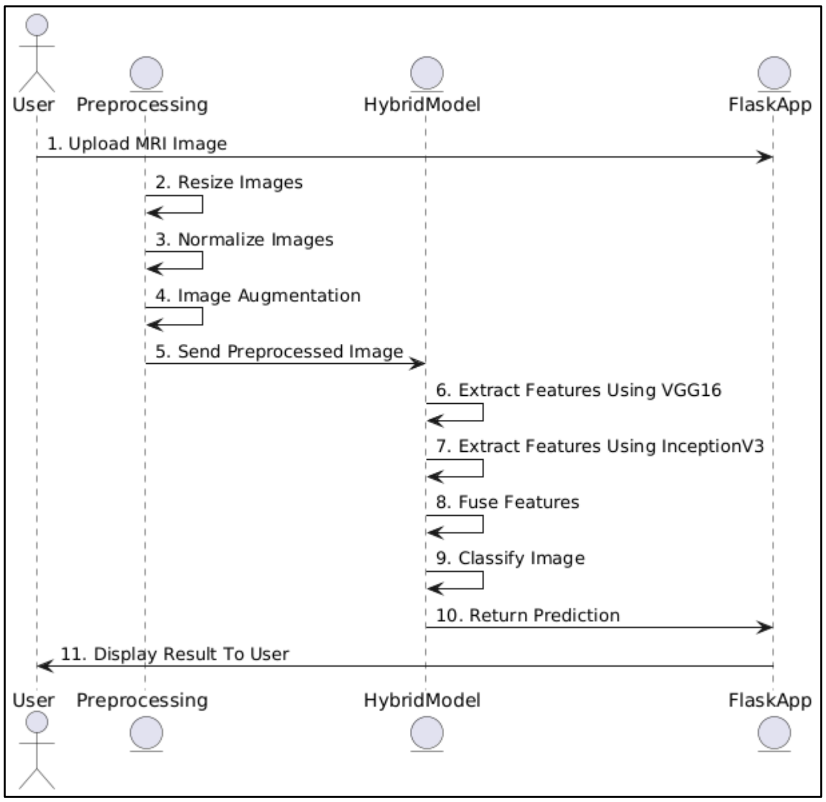

Figure 3.6: Sequence Diagram

This figure 3.6 gives sequence diagram that shows the interaction among the different components of the Brain Tumor Detection System from the user uploading an MRI image to the user getting the prediction result. Once the User uploads an MRI image, the Preprocessing module is called. Data preprocessing steps are resising image to a fixed size, pixel values normalization and some data augmentation techniques to provide more diversity in the dataset and improve model generalization ability. The image is then passed into the Hybrid Model component to complete the further processing.

In the Hybrid Model, two deep learning architectures (VGG16 and InceptionV3) independently extract the features of the image. The entire image is then fused from these features into a holistic representation, encompassing both fine-grained details and global patterns. This fusion process allows the model to capture a comprehensive understanding of the image's content. Next, the fused features are passed to the classification step, where the model classifies the image as either "tumor" or "not a tumor."

After classification, the prediction is sent back to the FlaskApp component. The FlaskApp then displays the tumor classification result to the user, ensuring clear communication of the diagnosis. This seamless interaction between image preprocessing, feature extraction, model classification, and result presentation creates an efficient and real-time brain tumor detection process, making it a valuable tool for medical practitioners. It guarantees rapid and accurate analysis, decision-making for patient care.

3.1.7 COMPONENT DIAGRAM

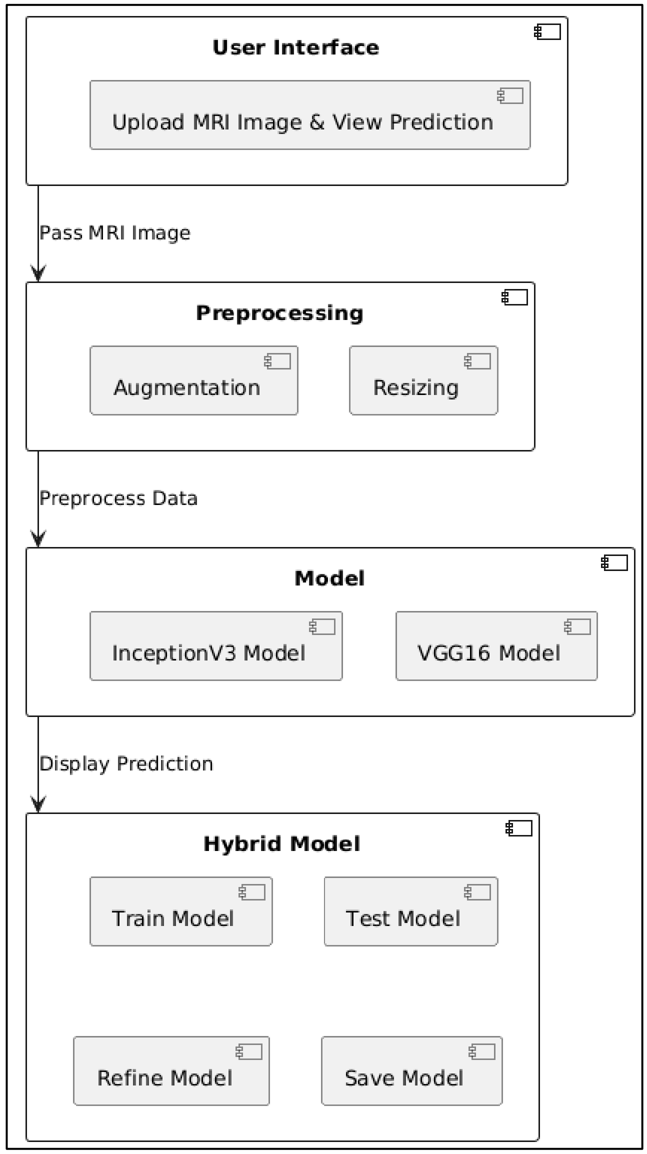

Figure 3.7: Component Diagram

This figure 3.7 outlines the component diagram of a hybrid brain tumor detection system. Users can upload MRI images and see predictions within the User Interface. Data is Preprocessed, including augmentation and resizing, and uploaded images. The Model uses InceptionV3 and VGG16 both for feature extraction. Finally, the Hybrid Model trains, refines, tests and saves the results for prediction and display purposes.

3.1.8 COLLOBORATION DIAGRAM

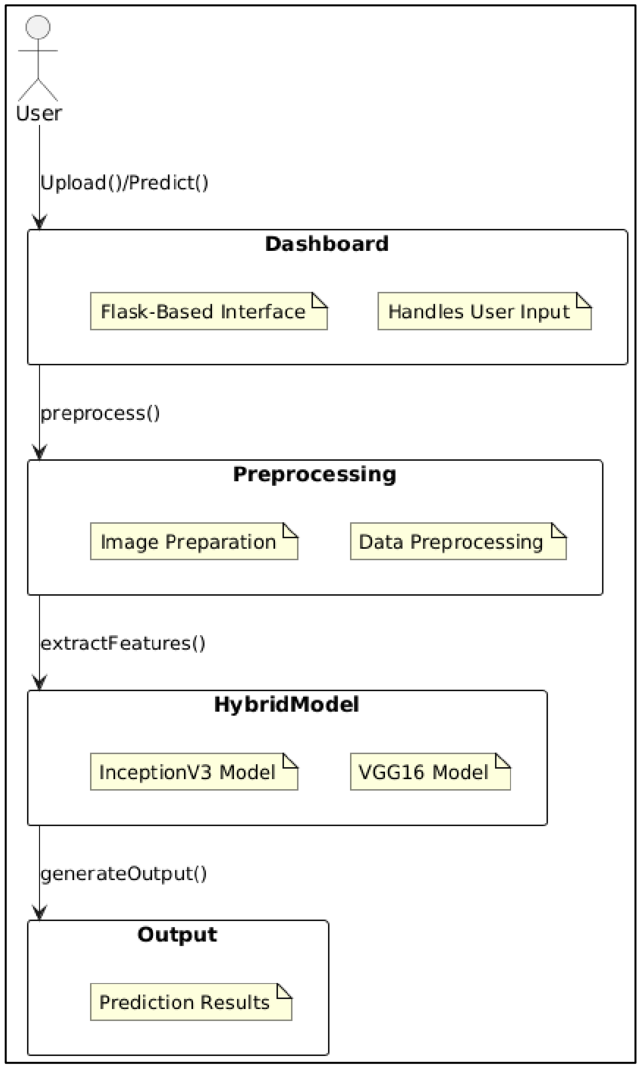

Figure 3.8: Colloboration Diagram

This figure 3.8 gives colloboration diagram of the system.This is a Flask based interface handling user input in the form of MRI images, that the User uploads through the Dashboard. Then the data moves to the Preprocessing stage where we perform image preparation and data preprocessing. The HybridModel is used to extract features, but the FeatureExtractor is combined using InceptionV3 and VGG16 models. The system then outputs the Output, displaying prediction results to the user.

CHAPTER 4

PROJECT DESCRIPTION

4.1 METHODOLOGIES

The methodology for developing and implementing the hybrid brain tumor detection system follows a systematic and structured approach to address the difficulty in detection of brain tumors. The process is organized into several stages, from problem identification to deployment and continuous system improvement, ensuring an effective solution on brain tumor detction.

4.1.1 MODULES

1. DATASET PREPARATION

This project is built upon the dataset preparation module. It involves organizing and categorizing MRI brain pictures into two distinct classes: Tumor and No Tumor. The standardized format (.jpg) of each image is used, and all pictures are resized to a uniform resolution of 150x150 pixels so that they are compatible with the machine learning models. Not only does this resizing simplify the computational processing, but also it keeps the clarity of the important features that are necessary for the classification. The dataset is split into two subsets: It has 80% for training and only 20% for validation so that the model has enough data to train from considerably less, while reserving a piece of that data for testing the model. It is necessary to divide this systematically to evaluate the model's ability to generalize on unseen data. The module minimizes potential bias by offering a balanced dataset across both classes.

2. DATA PREPROCESSING

A lot of data preprocessing is involved in preparing pictures to be trained by a machine learning model. So by increasing the quality and variety of the dataset the model generalizes from more and the risk of overfitting decreases. One popular set of techniques for image augmentation are flipping, rotating, and adjusting brightness, which greatly enhance the diversity of the training set and thus make for healthier models that are more robust to real world data.

Image Flipping : The image flipping is to horizontally or vertically flip the image. In particular, this technique is useful for simulating real world variations in how objects (or tumors, in this case) might look at different orientations. The pictures can have tumors on either side, and flipping the pictures during training helps the model recognize patterns that don't matter as long as they don't flip. By increasing the model's ability to generalize to unseen data, this. In addition to orientation, flipping also provides spatial structure variation, which allows less sensitive to spatial location and better feature extraction from different perspectives.

Rotating Pictures : Another powerful augmentation technique known as rotation augments by rotating pictures at random angles. It makes the model invariant to changes in the image orientation. In medical imaging, it is important for the model to not care about the angle an MRI scan is taken from, and still be able to identify tumors.

The model is able to detect features from different orientations by rotating them. For MRI scans, where the brain can be viewed from different angles, and a tumor may appear differently, this is particularly important.

Changing Brightness: Brightness adjustment is the technique that increases or decreases the brightness of the image slightly. Medical imaging devices like MRIs scans may capture pictures under different lighting conditions, causing the image to be less clear, or some features difficult to see. By preproccessing brightness, the model becomes less sensitive to lighting conditions.

3. FUSION AND FEATURE EXTRACTION

A big step towards endowing a deep learning model with the ability to learn in an unsupervised manner is feature extraction where deep learning models are used to learn meaningful patterns in input pictures. In this methodology, two highly efficient pre trained convolutional neural networks, VGG16 and InceptionV3 are utilized. VGG16 is well known for its simplicity and uniform architecture, a deep stack of convolutional layers with small 3x3 filters that well capture hierarchical feature such as edges and textures. Here, InceptionV3 uses more complicated architecture that feeds the input data through inception module in order to analyze the data at different scales all at once.

InceptionV3 also has its own ability to recognize more complex and more varied image features that make use of this capability. Both models are pre trained on the ImageNet dataset, so they already have a strong base of how to identify general image features. In this case, they remove their classification layers, keeping only their feature extraction layers. The models are adjusted in such a way that they should not make any predictions but rather extract useful image representations. We concatenate the feature maps from VGG16 and InceptionV3 in order to merge the strengths of both feature maps.

The combination together offers a richer (more diverse) representation of the input pictures, InceptionV3 adds multi-scale analysis, VGG16 contributes detailed spatial information. This fusion of both models produces a hybrid representation that contains complementary characteristics of other models. We achieve this improvement by simply adding the simplicity of VGG16 to the advanced multi scale analysis of InceptionV3 to obtain a hybrid model that is more robust and effective in distinguishing tumor pictures from non tumor ones.

4. MODEL TRAINING AND EVALUATION

The core phase of developing any machine learning solution with deep learning models for medical image classification is model training and evaluation. In this module we train and rigorously evaluate the performance of the hybrid model in optimizing this model for brain tumor detection using prepared datasets.

We fine tune the hybrid model which involves feature maps form VGG16 and InceptionV3 using the Adam optimizer. Because Adam is efficient with sparse gradients and can learn dynamically changing learning rates, Adam is chosen. We use binary cross entropy as our loss function for training which is appropriate for a binary classification problem such as this. Every epoch contains a training of which batches of input pictures goes into the model, loss values are calculated and weights are updated through back propagation. During this process appropriate metrics such as accuracy, precision, recall and the F1 score are being tracked to see how things are going.

Finally, validation is done at the end of every epoch so that we know that those improvements that we are seeing during the training are not due to memorization, but are actually indicative of the model's ability to generalize. This is addressed with the validation results being critical and techniques such as early stopping are implemented.It stops the training when validation accuracy no longer increases and starts to decrease, making certain that the produced model is both biased and variable detective of the model's ability to generalize. The validation results are critical for detecting overfitting to address this, techniques such as early stopping are implemented. It halts training when the validation accuracy stagnates or begins to decline, ensuring that the final model strikes the right balance between bias and variance. The module also includes callbacks to improve the training process.

These are callbacks that listen to the training metrics and automatically save the best model checkpoint based on validation accuracy, so the trained hybrid model is selected for deployment and it concludes. To address this, techniques such as early stopping are implemented to the validation results which are critical to detecting overfitting.Training is halted when the validation accuracy no longer increases or, at the very edge of this maximally biased and variance minimized condition, even begins to decrease, preventing the final model from being too biased or too variance excessive performing model checkpoint according to validation accuracy.The trained hybrid model is selected for deployment and it concludes movements observed during training are not due to memorization but are genuinely reflective of the model has ability to generalize its ouput.

Validation results are critical for detecting overfitting to address this, techniques such as early stopping are implemented. It halts training when the validation accuracy stagnates or begins to decline, ensuring that the final model strikes the right balance between bias and variance. The module also has callbacks for improving the training process. These callbacks monitor training metrics and automatically save the best-performing model checkpoint based on validation accuracy. It concludes with the selection of the trained hybrid model for deployment. A detailed evaluation is performed to validate that the model is robust and accurate, and ready to be applied by healthcare professionals for diagnosing brain tumors from MRI scans, enabling impactful real world applications.

5. USER INTERFACE MODULE

The brain tumor detection project user interface module takes advantage of Flask to provide a dynamic and interactive platform for users. This is a bridge between our machine learning model and end users so that we can receive input and deliver output. Flask is lightweight enough and versatile enough to be deployed as a machine learning application. Users are able to upload medical pictures through a web page, developed with an intuitive and user friendly design.

In the backend, Flask processes the image uploaded by a user, using the same preprocessing steps that we applied when training the model, like resizing and normalization. The hybrid model (VGG16 and InceptionV3) is used to predict whether there is a tumor after preprocessing. To satisfy architectural requirements, the model goes through the input both the original and a duplicated version of the input, and produces predictions mapped to class labels like 'Tumor' or 'No Tumor.' On a results page, these predictions help users get immediate feedback and better user experience. Error handling mechanisms prevent invalid uploads (unsupported file type or no submission) to send users into a black hole of error where they can’t read the error message. The Flask based interface makes it accessible to use by healthcare professionals who do not need to be experts in programming.

5.6 VISUALIZATION

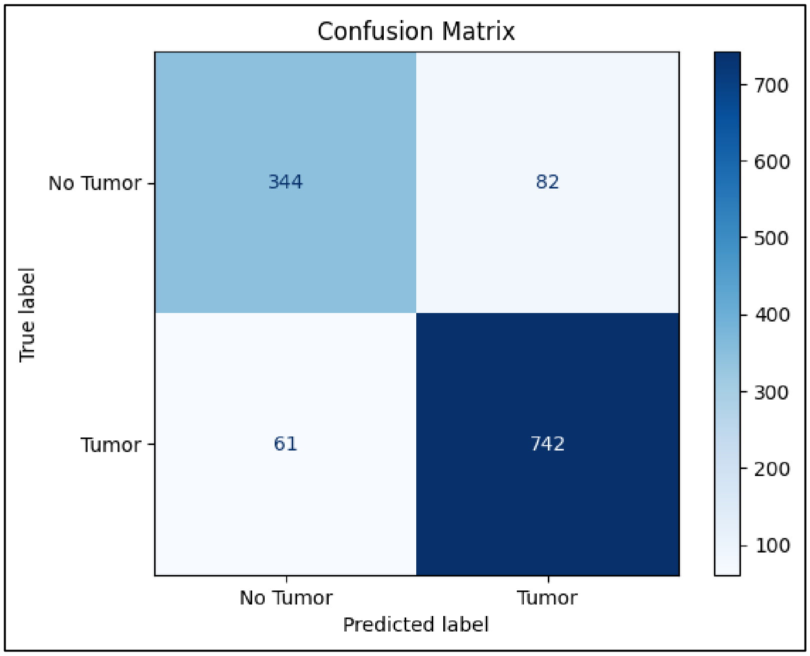

Figure 5.1 Confusion Matrix Diagram

This figure 5.1 visually represents the performance of a classification model in distinguishing between two classes: "No Tumor" and "Tumor." The predicted labels are on the columns and the actual (true) labels are on the rows. True negatives (correctly predicted as "No Tumor") are represented by the top left value (344), and true positives (correctly predicted as "Tumor") by the bottom right value (742). The false positives (cases incorrectly predicted as 'Tumor' when they were 'No Tumor') are represented by the top right value (82). False negatives (cases predicted as "No Tumor" when they were "Tumor") are represented by the bottom left value (61). The darker shades in the color intensity reflect the count in each cell. The model correctly classifies a large majority of instances with relatively few misclassifications, and the matrix illustrates that.

	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 5.2 Performance Metrics

This figure 5.2 gives a detailed evaluation metrics of the classification model's performance for two classes: "No Tumor" and "Tumor." The 'Precision' metric,given as the percentage of true predictions ver total predictions in all instances of a class, takes positive value of 0.75 for 'No Tumor' and 0.90 for 'Tumor'. Recall is the proportion of correct positives that are correctly identified and has higher recall for 'No Tumor' (0.85) than for 'Tumor' (0.82). This metric, called "F1-score", is a mean of its precision value and its recall value, and balances the metrics; the values for "No Tumor" and "Tumor" are 0.80 and 0.86, respectively. This means that in the "Support" column, 405 instances of "No Tumor" and 906 instances of "Tumor." Across all 1,311 samples, the model is accurate 83% of the time, or 0.83, meaning that it correctly classifies 83% of the samples. It highlights the model's effectiveness while suggesting room for improvement, especially in precision and recall for the "No Tumor" class.

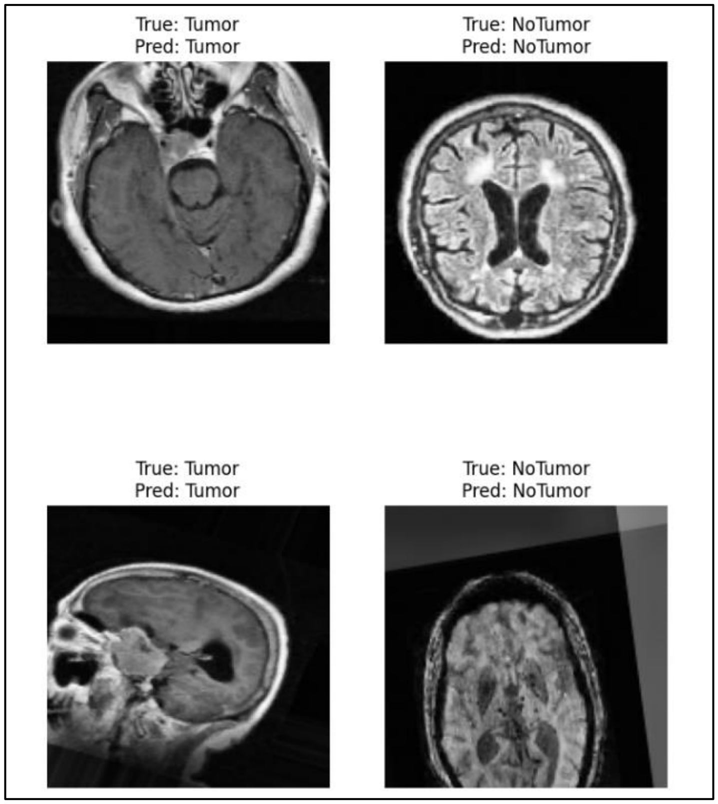

Figure 5.3 True Vs Prediction Diagram

This figure 5.3 gives grid of brain MRI pictures that classifies the true class (Tumor or No Tumor) along with predicted class by the model is labelled to each image. Correct predictions (e.g., "True: The model is able to accurately classify the scans, with error, if any, indicating misclassifications (Tumor, Pred: Tumor" or "True: No Tumor, Pred: No Tumor"). Finally, the visual presentation gives a qualitative assessment of how the model performs on these examples from the dataset. This enables an evaluation of how the model can be used to make sense of complex or ambiguous cases and additionally verifies if there are clear patterns of successful or incorrect predictions.

CHAPTER 5

CONCLUSION AND WORK SCHEDULE FOR PHASE II

5.1 CONCLUSION

In this project we present a hybrid deep learning model, using VGG16 and InceptionV3 to classify brain MRI pictures into tumor or no tumor classes. The model combines the strengths of both architectures, and shows improved accuracy and robustness over standalone systems. The limitations of data scarcity and the lack of reliable model are overcome using preprocessing techniques and data augmentation. Evaluation metrics show that the system is successful in detecting brain tumors, and provides a useful tool for radiologists to help them make timely and correct diagnoses.

5.2 FUTURE ENHANCEMENT FOR PHASE II

The current hybrid model performs well in separating tumor and non tumor categories, but there is room for improvement in the diagnostic capability of this model. The future work could expand its range of classification to classify specific tumor types, for example, glioma, meningioma, or pituitary tumors, and improve its ability to distinguish subtle differences. A user friendly interface supports the integration of the model into clinical workflows, allowing radiologists to upload MRI scans, view results and classify images. By prioritizing both usability and accuracy, healthcare professionals will be empowered to quicker, better decisions. To support clinical decision making effectively, it should remain focused on ensuring real world applicability.

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APPENDIX 1

TITLE: Integrating Hybrid Deep Learning Architectures For Accurate Brain Tumor Classification

AUTHORS: Dr. R. Bhuvaneswari, Madhan. B, Mohamed Basman. M

PUBLICATION STATUS:

Making the paper ready for the conference.

APPENDIX 2

```
# Params
EPOCHS = 35
BATCH_SIZE = 32
SHUFFLE = True
IMAGE_SIZE = (150, 150)
import zipfile
import os

# Define the path to the zip file and the target directory
zip_file_path = '/content/BrainDataset.zip'
extract_dir = '/content/BrainDataset'

# Unzip the dataset
with zipfile.ZipFile(zip_file_path, 'r') as zip_ref:
    zip_ref.extractall(extract_dir)

import numpy as np
from tensorflow.keras.preprocessing.image import
ImageDataGenerator
from tensorflow.keras.utils import Sequence
import cv2

def apply_clahe(image, clip_limit=2.0, tile_grid_size=(8, 8)):
    """Apply CLAHE to a single channel or RGB image."""
```

```
    if image.ndim == 2:  # If the image is grayscale
        # Ensure the image is 8-bit
        if image.dtype != np.uint8:
            image = image.astype(np.uint8)
        clahe = cv2.createCLAHE(clipLimit=clip_limit,
tileGridSize=tile_grid_size)
        return clahe.apply(image)
    elif image.ndim == 3 and image.shape[-1] == 3:  # If the image is
RGB
        img_yuv = cv2.cvtColor(image, cv2.COLOR_RGB2YUV)
        y, u, v = cv2.split(img_yuv)
        clahe = cv2.createCLAHE(clipLimit=clip_limit,
tileGridSize=tile_grid_size)
        cl = clahe.apply(y)
        yuv_clahe = cv2.merge([cl, u, v])
        return cv2.cvtColor(yuv_clahe, cv2.COLOR_YUV2RGB)
    else:
        raise ValueError("Unsupported image format")


class CLAHEImageDataGenerator(Sequence):
    """Custom data generator that applies CLAHE to images."""
    def __init__(self, image_data_generator, directory, target_size,
batch_size, class_mode='binary', shuffle=True, clip_limit=2.0,
tile_grid_size=(8, 8)):
        # Initialize the base class
        super().__init__()
```

```
        # Store parameters
        self.image_data_generator = image_data_generator
        self.directory = directory
        self.target_size = target_size
        self.batch_size = batch_size
        self.class_mode = class_mode
        self.shuffle = shuffle
        self.clip_limit = clip_limit
        self.tile_grid_size = tile_grid_size

        # Initialize the data generator
        self.data_gen =
self.image_data_generator.flow_from_directory(
            directory=self.directory,
            target_size=self.target_size,
            batch_size=self.batch_size,
            class_mode=self.class_mode,
            shuffle=self.shuffle
        )
        self.class_indices = self.data_gen.class_indices  # Store class
indices

    def __len__(self):
        return len(self.data_gen)
```

```
    def __getitem__(self, index):
        x_batch, y_batch = self.data_gen[index]
        x_batch_clahe = np.zeros_like(x_batch)
        for i in range(x_batch.shape[0]):
            x_batch_clahe[i] = apply_clahe((x_batch[i] *
255).astype(np.uint8), clip_limit=self.clip_limit,
tile_grid_size=self.tile_grid_size) / 255.0
        return x_batch_clahe, y_batch


    def on_epoch_end(self):
        if self.shuffle:
            self.data_gen.on_epoch_end()
import matplotlib.pyplot as plt
from tensorflow.keras.preprocessing.image import load_img,
img_to_array


def display_original_and_preprocessed(image_path, target_size,
clip_limit=2.0, tile_grid_size=(8, 8)):
    """Displays the original and CLAHE-preprocessed images side
by side."""
    # Load and preprocess the image
    # Check if the file exists before trying to load it
    if not os.path.exists(image_path):
        print(f"Error: Image not found at {image_path}")
        return  # Exit the function if the image is not found
```

```
    original_img = load_img(image_path, target_size=target_size)
    original_img_array =
img_to_array(original_img).astype(np.uint8)

    # Apply CLAHE preprocessing
    preprocessed_img = apply_clahe(original_img_array,
clip_limit=clip_limit, tile_grid_size=tile_grid_size)

    # Display the images
    plt.figure(figsize=(10, 5))

    # Original Image
    plt.subplot(1, 2, 1)
    plt.title("Original Image")
    plt.imshow(original_img_array.astype(np.uint8))
    plt.axis('off')

    # Preprocessed Image
    plt.subplot(1, 2, 2)
    plt.title("Preprocessed Image")
    plt.imshow(preprocessed_img.astype(np.uint8))
    plt.axis('off')

    plt.show()
```

```
# Example usage

example_tu='/content/BrainDataset/Training/Tumor/Tr-tu_1.jpg'
example_no='/content/BrainDataset/Training/No Tumor/Tr-no_1.jpg'

display_original_and_preprocessed(example_tu, target_size=(150, 150))
display_original_and_preprocessed(example_no, target_size=(150, 150))
from tensorflow.keras.applications import VGG16, InceptionV3
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Dense, Dropout, Flatten, concatenate, BatchNormalization, GlobalAveragePooling2D

def create_pretrained_model_1(input_shape):
    base_model = VGG16(weights='imagenet', include_top=False, input_shape=input_shape)

    for layer in base_model.layers[:10]:
        layer.trainable = False

    for layer in base_model.layers[10:]:
        layer.trainable = True

    x = base_model.output
```

```
    x = GlobalAveragePooling2D()(x)
    x = Dense(256, activation='relu')(x)
    x = Dropout(0.5)(x)

    return base_model.input, x

def create_pretrained_model_2(input_shape):

    base_model = InceptionV3(weights='imagenet',
include_top=False, input_shape=input_shape)

    for layer in base_model.layers[:10]:
        layer.trainable = False

    for layer in base_model.layers[10:]:
        layer.trainable = True

    x = base_model.output
    x = GlobalAveragePooling2D()(x)
    x = Dense(256, activation='relu')(x)
    x = Dropout(0.5)(x)
    return base_model.input, x

def create_hybrid_model(input_shape):
    input_1, output_1 = create_pretrained_model_1(input_shape)
```

```
    input_2, output_2 = create_pretrained_model_2(input_shape)

    combined = concatenate([output_1, output_2])
    z = Dense(256, activation='relu')(combined)
    z = Dropout(0.5)(z)
    z = Dense(1, activation='sigmoid')(z)

    model = Model(inputs=[input_1, input_2], outputs=z)
    return model

input_shape = (150, 150, 3)
hybrid_model = create_hybrid_model(input_shape)
hybrid_model.summary()
```

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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:

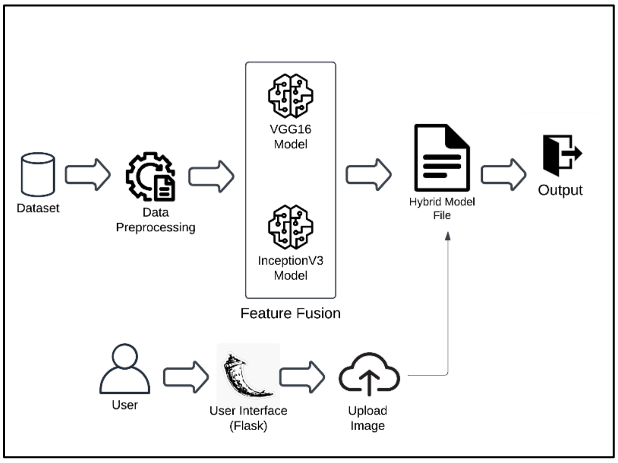

Figure 3.1 Architecture Diagram

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

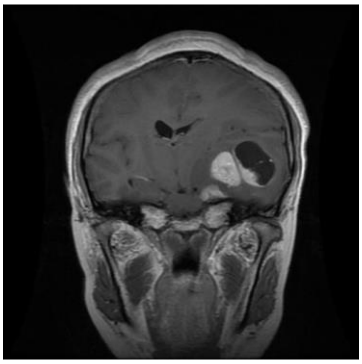

Figure 3.4

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.

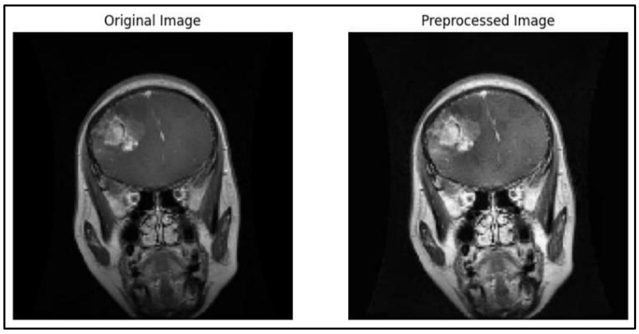

Figure 3.5

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.

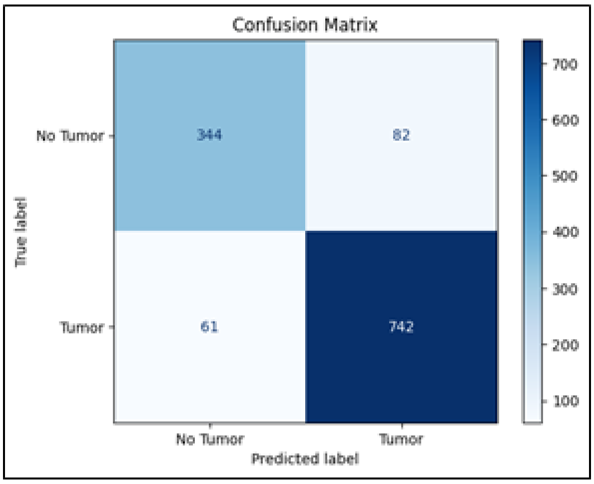

Figure 4.2 Confusion Matrix Diagram

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.

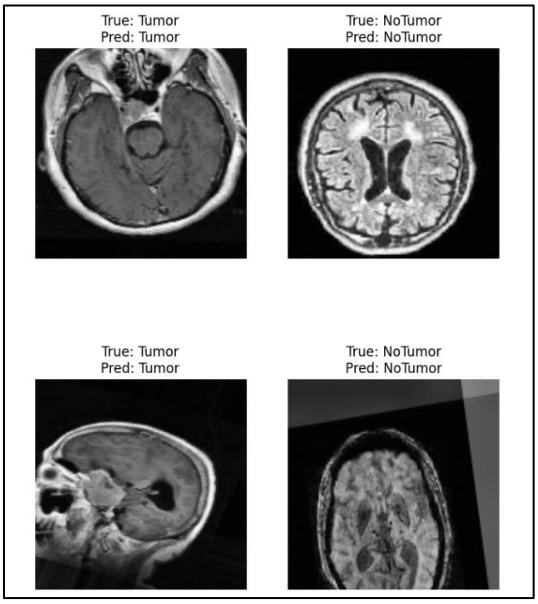

Figure 4.2 True Vs Prediction Diagram

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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