MEDICAL IMAGE CLASSIFICATION: A MULTIMODEL APPROACH WITH EXPLAINABLE MODELS

Project Submitted to the
SRM University AP, Andhra Pradesh
for the partial fulfillment of the requirements to award the degree of

Bachelor of Technology
in
Computer Science & Engineering
School of Engineering & Sciences

submitted by

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May 2024

DECLARATION

The undersigned hereby certifies that the project report **Medical Image Classification: A Multimodel Approach with Explainable Models submitted for partial fulfillment of the requirements for the award of the degree of Bachelor of Technology in the Computer Science & Engineering, SRM University-AP, is a bonafide work done by us under the supervision of & . This submission represents our ideas in our own words and where ideas or words of others have been included, we have adequately and accurately cited and referenced the sources. We also declare that we have adhered to ethics of academic honesty and integrity and have not misrepresented or fabricated any data or idea or fact or source in my submission. We understand that any violation of the above will be a cause for disciplinary action by the institute and/or the University and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been obtained. This report has not been previously formed the basis for the award of any degree of any other University.**

Place	**: Amaravathi Date: May 12, 2024**
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CERTIFICATE

This is to certify that the report entitled **Medical Image Classification: A Multimodel Approach with Explainable Models** submitted by **BADDELA GEETHESWAR REDDY, TURJA BHATTACHARJEE, DEEPAK SAI PUSUKURI, GEEDA ADITHYA REDDY** to the SRM University-AP in partial fulfillment of the requirements for the award of the Degree of Bachelor of Technology in is a bonafide record of the project work carried out under my/our guidance and supervision. This report, in any form has not been submitted to any other University or Institute for any purpose.

Project Guides

Signature:	Signature: ....
Name :	Name :

....

Prof. Niraj Upadhayaya

Head of Department, Department of Computer Science & Engineering

ACKNOWLEDGMENT

I wish to record my indebtedness and thankfulness to all who helped me prepare this Project Report titled **Medical Image Classification: A Multimodel Approach with Explainable Models** and present it satisfactorily.

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ABSTRACT

This extensive research delves into the intersection of MRI imaging and deep learning, in the task of identifying and categorizing brain tumors. In addition to models like VGG16 and ResNet101 a designed Convolutional Neural Network (CNN) was developed and thoroughly evaluated showcasing a range of techniques utilized. Augmentation methods were purposefully applied to enrich the dataset, enhancing the models robustness and adaptability. Evaluation metrics, including the F1 score, recall, accuracy, and precision gave a general picture of the model's performance. Furthermore leveraging Explainable AI (XAI) techniques such as LIME unveiled insights, into the decision making processes underlying the models enhancing their interpretability and trustworthiness. The studys findings ultimately underscore the potential of learning in revolutionizing automated brain tumor diagnosis and classification poised to enhance patient care pathways and medical diagnostic capabilities significantly.

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Chapter 1

INTRODUCTION TO THE PROJECT

Brain tumours, where a mass of cells grows abnormally within the brain, are a major medical challenge since they might be either malignant (cancerous) or benign (non-cancerous). Successful treatment plans and better patient prognosis can only be achieved through immediate accurate diagnosis. The dangers inherent in traditional diagnostic methods like biopsies accentuate the need for safe and non-invasive diagnostics. In this case, Deep learning may work as a technique of identifying and classifying brain tumors. It uses its capacity to locate intricate patterns in data in order to provide an applicable solution to analyzing magnetic resonance imaging (MRI) and other medical imaging modalities.

They have the ability to distinguish tumor-free brain tissues from those affected by them, which is an incredible feat that will change the entire diagnostic process making it more individualized and targeted. Tumors come in three main types: benign, malignant and metastatic. This means that it spreads slowly with no harmful effects on other tissues or penetration into them hence called non-cancerous tumors. Malignant tumors also known as cancerous growths.

1.1 AIM OF THIS PROJECT

The goal of this research is to develop a deep learning model that uses MRI images to precisely identify and diagnose brain tumors. In order to train and evaluate this model, it will be provided with a set of labeled MRI images and compared against existing methods. The model will learn through recurrent adjustment to identify subtle features which signify different types of cancer. Stringent evaluation in relation with predetermined benchmarks shall validate its usefulness. Eventually, the aim of our project is to enhance brain cancer diagnosis by allowing medical practitioners access a tool that enhances treatment plans and patient outcomes efficiently.

1.2 SCOPE

The primary objective of this research is to develop an advanced deep learning model specifically intended for the identification and classification of brain cancers from MRI images. There are numerous steps in the process:

1. Data preprocessing is the meticulous preparation of the dataset through operations like gray scale image conversion, picture scaling and cropping for consistency, color map incorporation for improved display, and noise reduction filter application for improved image clarity.

2. Data augmentation involves applying operations like zooming on the dataset in order to increase its size and strengthen the model's capacity to withstand variations in the input data.

3. Model Development: Examining several deep learning architectures to determine which is best for a given job, from well-known models like ResNet101 and VGG16 to a specially-designed convolution neural

network

4. Model evaluation is the process of carefully evaluating a model's performance using a wide range of evaluation measures,to evaluate the model's performance and adaptability in different scenarios, such as the F1-score, recall, accuracy, and precision.

5. Explainable Models: using techniques such as LIME to decipher the model's underlying decision-making processes, clarifying the critical elements that lead to tumor diagnosis and improving interpretability.

6. Ensemble Learning: Exploring cutting-edge methods like Boosting and bagging to use the combined intelligence of several models in order to further improve prediction resilience and accuracy by combining a variety of viewpoints.

The research aims to advance automated brain tumor detection and classification by carefully traversing through each step of this extensive framework. This will eventually open the door for more precise diagnostic tools and better patient outcomes in clinical settings.

1.3 OBJECTIVES

The main goals of this study are to conduct a thorough analysis of deep learning methods in relation to magnetic resonance imaging (MRI)-based brain cancer detection and classification. These objectives include:

1. The creation of an exact deep learning model that can recognize and classify different kinds of MRI images for brain tumors.

2. A comparative analysis of the performance of several deep learning architectures, such as bespoke models and well-known frameworks

like ResNet101 and VGG16, in order to identify the best method for classifying brain tumors.

3. Research investigates how well data augmentation methods strengthen the model's resilience and generalizability, strengthening its capacity to correctly identify brain cancers in a variety of datasets.

4. Explainable AI (XAI) approaches are used to clarify the critical elements required for tumor identification, providing insight into the model's decision-making procedures and improving interpretability.

5. Ensemble learning is a machine learning approach that integrates the predictors from numerous separate models in order to get a superior predictive performance than any single model. By combining the predictions of several models-each of which may have advantages and disadvantages of its own ensemble learning aims to capitalize on the wisdom of the crowd

6. Investigating ensemble learning strategies to improve prediction accuracy and robustness to data fluctuation by utilizing the combined predictive capacity of many models, such as Boosting and bagging.

7. a comprehensive evaluation of the generated model's performance against existing methods that have been documented in the literature, providing enlightening details regarding its relative efficacy and potential for practical application.

This project aims to enhance patient care and clinical outcomes in the fields of medical imaging and oncology by methodically tackling these objectives and pushing the boundaries of automated brain cancer detection.

Chapter 2

MOTIVATION

We are driven by a profound desire to address the urgent need for a precise, non-invasive method of diagnosing brain tumors. Having personally experienced the difficulties presented by conventional diagnostic techniques, we were driven to investigate novel approaches at the nexus of technology and healthcare. We were attracted to the idea of using neural networks to analyze MRI images for tumor detection and classification because of the profoundly transformative potential of deep learning in medical imaging. With a strong sense of resolve and excitement, we set out on this adventure under the direction of our distinguished instructors, Drs. Pradyut Kumar Sanki and Pranab Mandal.Our enthusiasm for accountability and openness in healthcare technology was further stoked by the chance to contribute to Explainable AI (XAI) techniques. Our mission is to transform the diagnosis of brain tumors, improve patient outcomes, and boost clinical workflow efficiency overall. Our goal is to close the gap between technology and medicine through our research, positively influencing both patients' and healthcare providers' lives.

Chapter 3

LITERATURE SURVEY

Medical image analysis has undergone a paradigm shift as a result of the convergence of deep learning and MRI imaging, particularly in the area of brain tumor identification and classification. This review synthesizes current literature and highlights recent advancements, methodologies, and findings to examine the intersection of these two domains.

The ability of deep learning models, such as ResNet101, VGG16, and customized Convolutional Neural Networks (CNNs), to recognize and categorize brain tumors from MRI images has been demonstrated in recent studies. Through their ability to recognize intricate patterns in imaging data, these models offer a potential solution to the limitations of traditional diagnostic methods like biopsies.

Deep learning models have been made more resilient and adaptive through the use of augmentation techniques, which enrich datasets. Researchers guarantee standardized input for model training by preprocessing data and applying operations like color mapping and noise reduction, which improves performance across a variety of datasets.

Model performance is revealed by evaluation metrics like F1 score, recall, accuracy, and precision, which show high recall and precision rates for the majority of classes. Furthermore, explainable AI (XAI) approaches that enhance interpretability and reliability—like Local Interpretable Model-Agnostic Explanations (LIME)—make model decision-making processes transparent.

The results highlight deep learning's potential to transform automated brain tumor classification and diagnosis. Researchers hope to greatly improve patient care pathways and medical diagnostic capabilities by utilizing cutting edge techniques and methodologies.

In order to further increase prediction accuracy and robustness, future research directions include investigating ensemble learning techniques like bagging and boosting. Furthermore, group learning research and the incorporation of other XAI techniques have the potential to improve model interpretability and performance.

To sum up, the compilation of current research highlights how deep learning is revolutionizing medical imaging, especially when it comes to diagnosing brain tumors. Researchers hope to improve patient outcomes in clinical settings by developing more accurate and comprehensible diagnostic tools by pushing the limits of technology and methodology.

Chapter 4

METHODOLOGY

The research design involved a comprehensive assessment of the utility of deep learning in ensuring accurate MRI scan based diagnosis and classification of brain tumor. Collection of MRI scans that do not have tumors and those with tumours was done carefully, which resulted to creation of an entire dataset. For example, in preprocessing, standardize picture formats and improve image quality such as noise reduction, color mapping and scaling among others. To increase diversity of datasets through augmentation approaches for model development various deep learning architectures like VGG16, ResNet101 and customized CNNs were created and trained on. Model performance was measured using evaluation measures like accuracy and precision, augmented by Explainable AI techniques such as LIME to understand decision-making processes. Boosting and bagging are two ensemble learning techniques investigated to improve model accuracy in concert. This methodological approach is aimed at improving the clinical decision-making process by revealing data processing confluence with disambiguation requirements as well as advancing automated brain tumor detection.

4.1 PROBLEM STATEMENT

Enhancing the ability to recognize and characterize brain cancer from MRI images is the aim. Conventional methods utilized in the diagnosis and initiation of treatment often delay the process as they require invasive procedures and subjective interpretations. Our study, therefore, aims at answering these gaps by introducing modern deep learning techniques that will guarantee precise diagnoses within short durations. In light of this, it is our aim to streamline the management of brain tumors for enhanced patient outcomes through the development of novel approaches such as automated analysis or pattern recognition.

4.2 REQUIREMENTS

4.2.1 Functional Requirements

An MRI image enters the system, and a preprocessing unit is responsible for formatting it into the appropriate mode of the deep learning model. This means that the algorithm should only detect one brain tumor in each input image. Moreover, these tumors can be classified as either: pituitary, meningioma, glioma, or the absence of any tumor. The results are then labeled with confidence scores, showing how confident they are about their classification. Therefore, this system explains why it has classified an image as such and increases interpretability for stakeholders and doctors while providing reasoning behind them.

4.2.2 Non-functional Requirements

4.2.2.(i) Accuracy

The framework is set up to exhibit a significantly high degree of accuracy in recognizing and classifying brain tumors, therefore assuring dependable diagnostic results. The swiftness with which input images are processed and findings are sent indicates that efficiency is emphasized, thereby reducing wait times for diagnosis as well as treatment planning purposes. User-friendliness is given priority by the system's interface, such that users can move around easily and get access to their information, including while putting in images; thus enhancing its usability. Users can rely on the system's results time after time because it has been designed to function consistently and reliably. Reliability is vital.

4.2.2.(ii) Feasibility Study

A thorough feasibility study was carried out to assess the project's viability, taking into account several key factors. The technical feasibility has been considered in depth to ensure that there are enough resources available, such as dependable deep learning frameworks, libraries and data sets for model training. This thorough evaluation of the project's economic viability showed that it is cost-effective due to availability of open sourced software and use of reasonably priced cloud computing platforms.

4.2.2.(iii) System requirements & Hardware Requirements

RAM (16GB), processor (Intel i7-12th Gen), GPU (GeForce RTX 1650Ti), and storage (10GB). These system requirements should be good enough on a machine that would be able to handle computational demands placed on it by deep learning models; programming language Python and its accompanying libraries like TensorFlow, Keras, OpenCV, scikit-learn, LIME etc. Development Environment such PyCharm or Jupyter Notebook or Google Colab.

Chapter 5

SYSTEM ARCHITECTURE

Three major, interconnected components make up the system's well-designed architectural framework, which enables the efficient identification and categorization of brain tumors from MRI images. The user's initial point of contact is the input interface, which has basic features for choosing or uploading MRI pictures. Subsequently, the preprocessing module executes essential functions like noise reduction, cropping, scaling, and color mapping to improve the quality of the input images. Additionally, a feature extraction module that takes identifiable features out of the pre-processed images can be used to use advanced deep learning models like VGG16, ResNet101, or custom CNNs to find subtle patterns that may indicate brain tumors. These components come together to form an integrated architecture that enables trustworthy and precise diagnosis and accurately grading brain tumors, enhancing clinical diagnostic capabilities while providing patient care.

Classification Module: One important aspect of this design is a classification module which uses information from the input image to assign it into one among different assigned tumor classes. By employing advanced algorithms such as those prevailing within the state-of-the-art machine learning technology, this module examines the unique features included in the image to enable precise categorization. The final part of this approach is completed by Explainable AI (XAI) module, which utilizes Local Interpretable Model-Agnostic Explanations (LIME), a cutting-edge technique for explaining The model's decision-making procedure. Improve interpretation and trust in system outputs can be achieved by using XAI, which allows users to determine which specific areas were considered during image classification. Finally, output interface shows the classification results and XAI explanations. Users receive detailed information such as confidence score and expected tumor type facilitating accurate clinical decisions making and supporting effective patient care techniques. A robust and transparent system architecture that has potential to overturn the understanding of clear-cut diagnosis and categorization of brain tumors combines all these factors in one place.

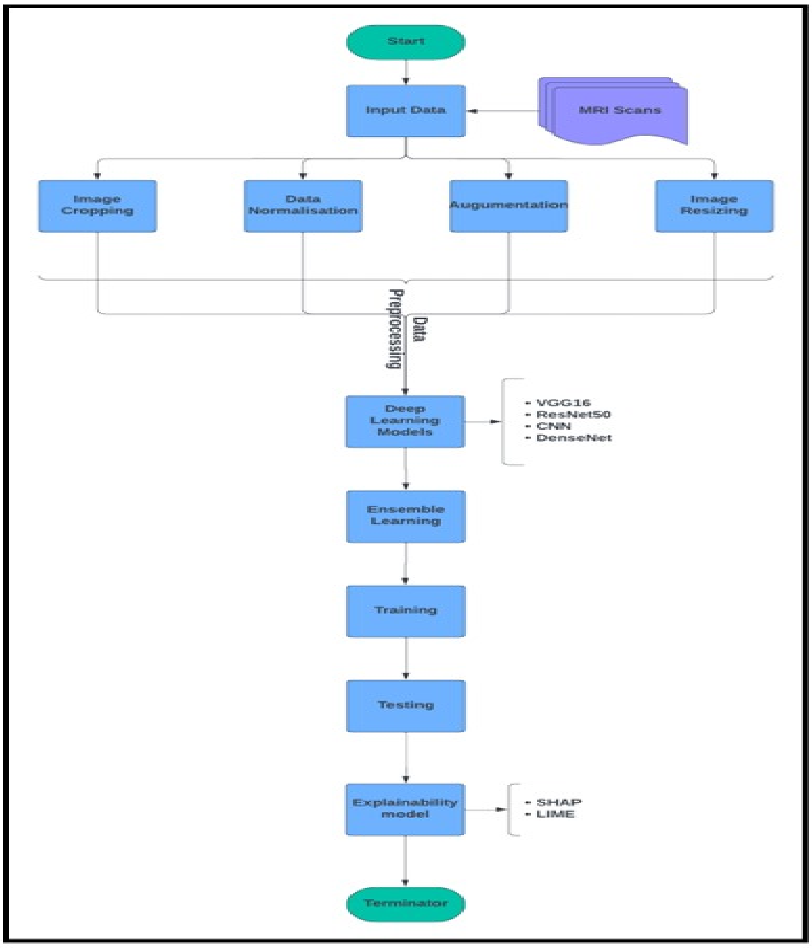


Figure 5.1: System Architecture.

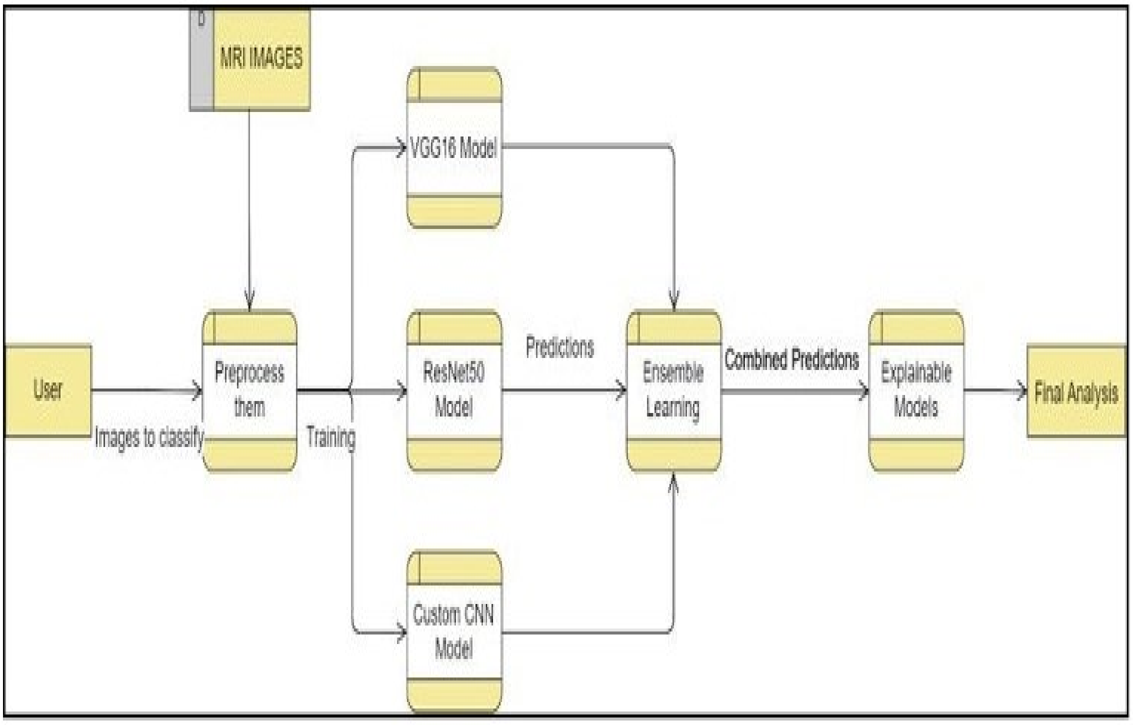


Figure 5.2: Data flow diagram.

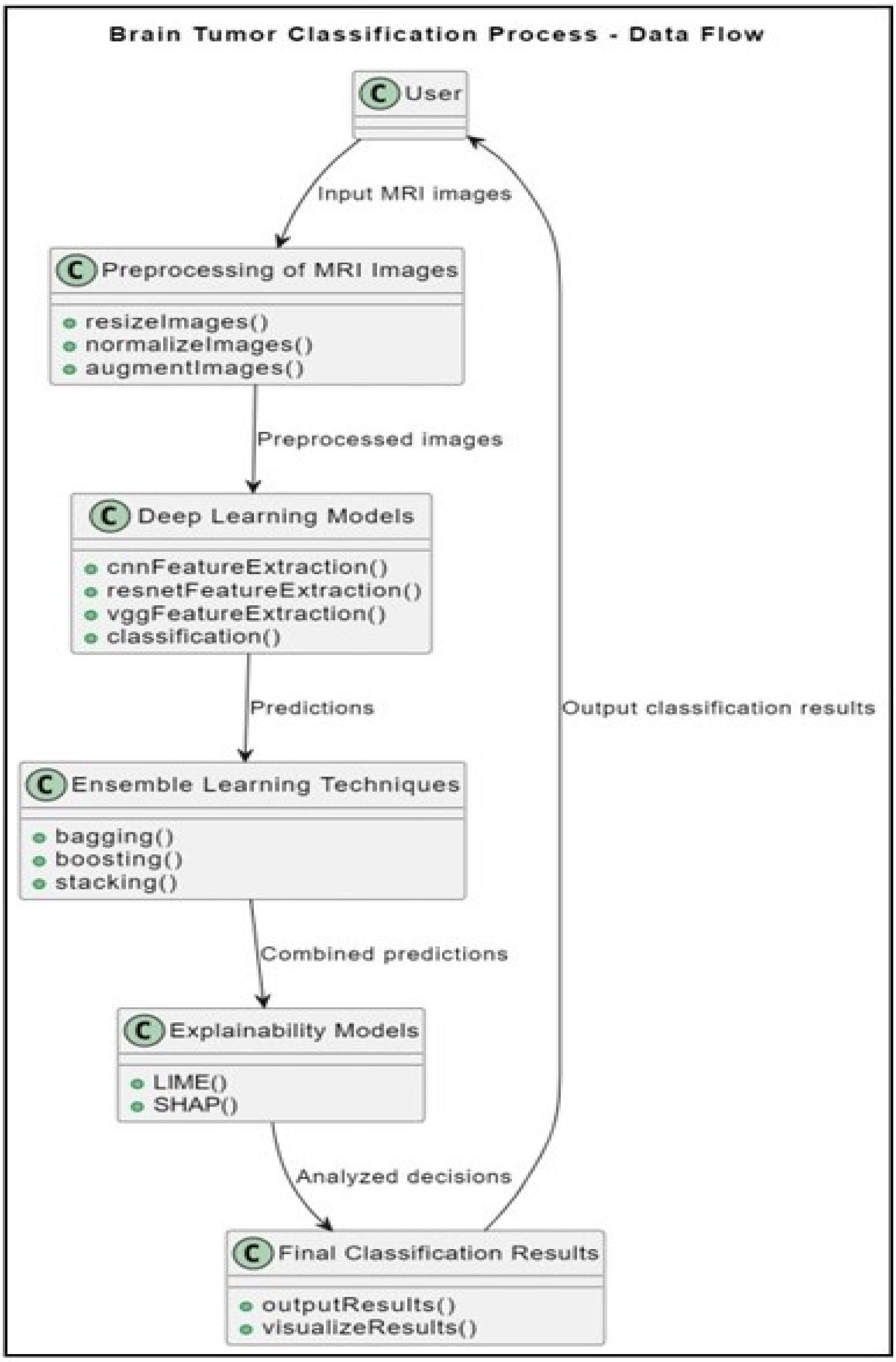


Figure 5.3: Class diagram.

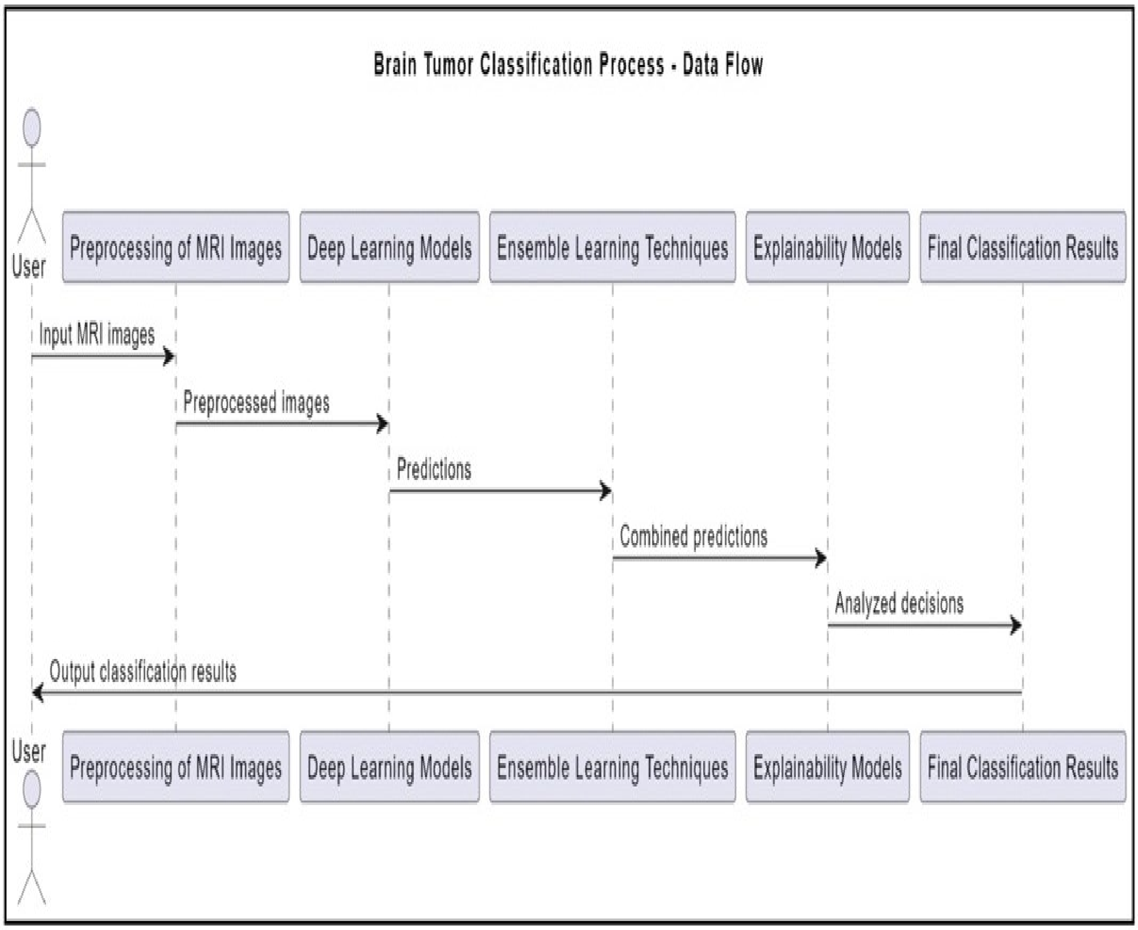


Figure 5.4: Sequence diagram.

Chapter 6

IMPLEMENTATION

Using MRI images, the project's implementation involved a methodical approach to leveraging deep learning's potential for precise brain tumor identification and classification. This is a thorough rundown of the implementation procedure:

6.1 DATA GATHERING AND PREPROCESSING

MRI scans from dependable sources were used to gather images showing both tumor-free and tumor-present states. Preprocessing of the gathered images included applying color mapping for better visualization, standardizing image formats, and improving image quality through noise reduction techniques. To improve the dataset's diversity and fortify the model's capacity for generalization, data augmentation techniques were utilized, such as zooming.

6.2 MODEL DEVELOPMENT

Various deep learning architectures were analyzed, such as pre-trained models such as VGG16 and ResNet101, and convolutional neural networks (CNNs) specifically designed for the task of brain tumor classification. The models were trained on the preprocessed and augmented dataset to identify features suggestive of different types of brain tumors, utilizing the rich patterns found in MRI images.

6.3 ASSESSMENT AND PERFORMANCE MEASURES

The performance of the trained models was evaluated using a variety of metrics, such as F1-score, Accuracy, Precision, and Recall. These metrics shed light on the models' general efficacy in clinical settings as well as their capacity to accurately categorize various kinds of brain tumors.

6.4 TECHNIQUES FOR EXPLAINABLE AI (XAI)

To understand how the models make decisions,explainable AI techniques were applied, such as Local Interpretable Model-Agnostic Explanations (LIME). By revealing the important characteristics and trends that the models took into account during classification, XAI techniques improved transparency and reliability.

6.5 STRATEGIES FOR COLLABORATIVE LEARNING

Boosting and bagging are two ensemble learning techniques that were looked into to improve prediction accuracy and model robustness even more. Across a range of datasets and scenarios, ensemble learning sought to enhance performance by merging the predictive powers of several models.

6.6 SYSTEM ARCHITECTURE AND INTEGRATION

The system architecture that was put into place was made up of interconnected parts, such as modules for preprocessing images to improve their quality, modules for feature extraction to detect tumors, modules for classifying images to determine the types of tumors, and modules for XAI to provide descriptions. The system was created with clinical workflows in mind, making it easy to integrate and guaranteeing accessibility and usability for medical professionals.

All things considered, the project's execution proved how powerful deep learning methods can be for improving automated brain tumor identification and categorization, opening the door for further developments in oncology and medical imaging.

Chapter 7

SOFTWARE TOOLS USED

This chapter discusses the details of the software tools used in the implementation of the project.

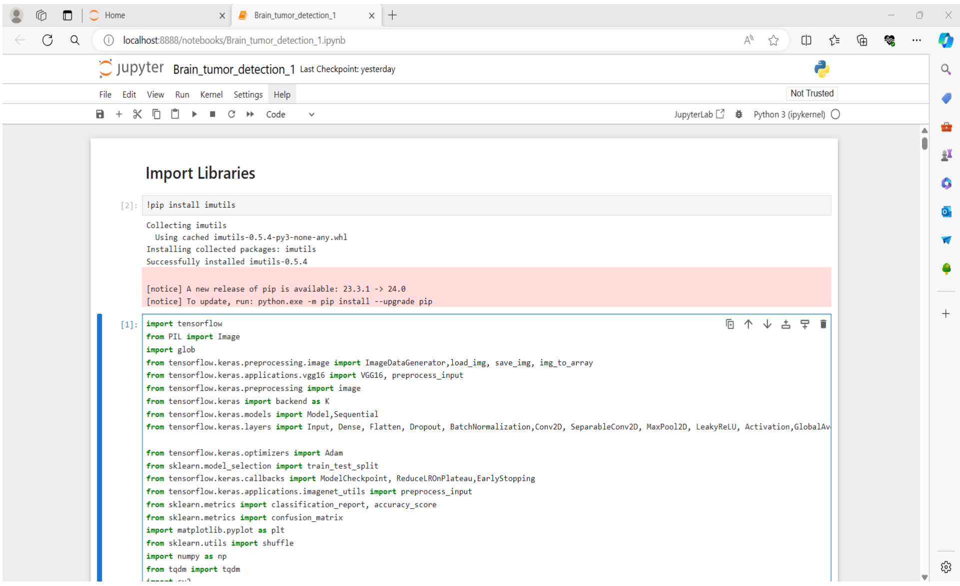


Figure 7.1: Jupyter Notebook

Chapter 8

RESULTS AND DISCUSSION

The below given classification report contains the evaluation results for the ensemble learning classification model with four classes: glioma, meningioma, notumor, and pituitary. Here's what each metric means:

8.1 PRECISION

Precision is defined as the ratio of true positive predictions to all positive predictions made by the model. It displays the percentage of cases that were, in fact, the anticipated class. For example, a precision of 0.98 for glioma means that out of all instances predicted as glioma by the model, 98% were correctly classified.

	precision	recall	f1-score	support
glioma	0.98	1.00	0.99	300
meningioma	0.98	0.98	0.98	306
notumor	0.99	0.98	0.99	405
pituitary	0.99	0.98	0.98	300
accuracy			0.98	1311
macro avg	0.98	0.98	0.98	1311
weighted avg	0.98	0.98	0.98	1311

Table 8.1: precision, recall, f1-score and support

8.2 RECALL

Recall is defined as the ratio of true positive predictions to the total number of cases that actually belong in that class. It displays the percentage of actual cases of a class that the model correctly predicted. For instance, glioma has a recall of 1.00, which indicates that 100

8.3 F1-SCORE

The F1-score is defined as the harmonic mean of recall and precision. It provides a balance between recall and precision, especially when the classes are not evenly distributed. It is computed as 2×Precision×RecallPrecision+Recall2× Precision+Recall(Precision×Recall). A higher value (which goes from 0 to 1) denotes better model performance.

8.4 SUPPORT

The number of samples that were present in each test set class is represented by the term support.

8.5 ACCURACY

Accuracy is defined as the ratio of correctly predicted instances to the total number of instances (across all classes). It measures the overall prediction accuracy of the model.

8.6 MACRO AVG

Precision, recall, and F1-score are the metrics that are averaged for each class in the macro average calculation; class imbalance is not taken into account. Every class is accorded equal weight.

8.7 WEIGHTED AVG

By weighting the metrics by the number of instances in each class, the weighted average determines the average of the metrics. By assigning greater weight to classes with more instances, it corrects for class imbalance.

In this instance, the model performs well, as evidenced by its high recall, precision, and F1-score for the majority of classes. The model's accuracy of 0.98 indicates that it makes accurate predictions.

Chapter 9

OUTPUT

brain-tumor-detection-1

April 26, 2024

0.1 Import Libraries

[2]:
```
!pip install imutils
```

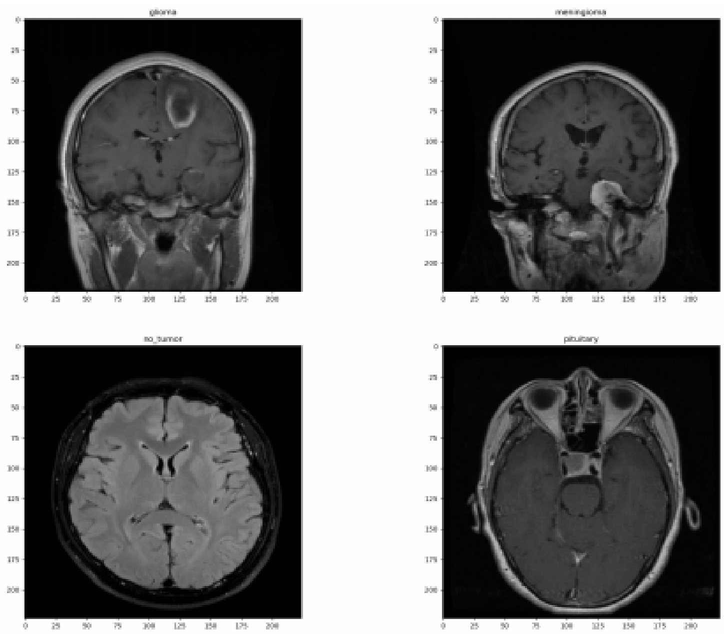
```
Collecting imutils
  Using cached imutils-0.5.4-py3-none-any.whl
Installing collected packages: imutils
Successfully installed imutils-0.5.4

[notice] A new release of pip is available: 23.3.1 -> 24.0
[notice] To update, run: python.exe -m pip install --upgrade pip
```

[ ]:

[1]:
```
import tensorflow
from PIL import Image
import glob
from tensorflow.keras.preprocessing.image import ImageDataGenerator,load_img,␣
↪save_img, img_to_array
from tensorflow.keras.applications.vgg16 import VGG16, preprocess_input
from tensorflow.keras.preprocessing import image
from tensorflow.keras import backend as K
from tensorflow.keras.models import Model,Sequential
from tensorflow.keras.layers import Input, Dense, Flatten, Dropout,␣
↪BatchNormalization,Conv2D, SeparableConv2D, MaxPool2D, LeakyReLU,␣
↪Activation,GlobalAveragePooling2D

from tensorflow.keras.optimizers import Adam
from sklearn.model_selection import train_test_split
from tensorflow.keras.callbacks import ModelCheckpoint,␣
↪ReduceLROnPlateau,EarlyStopping
from tensorflow.keras.applications.imagenet_utils import preprocess_input
from sklearn.metrics import classification_report, accuracy_score
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
from sklearn.utils import shuffle
import numpy as np
```

1

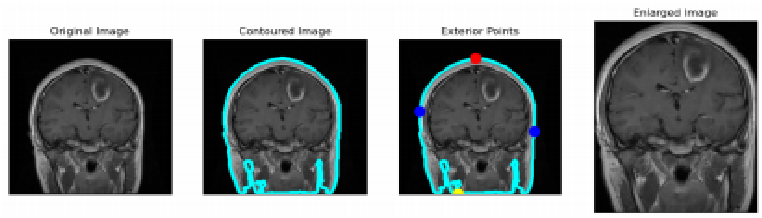
Figure 9.1: output 1



0.3 Cropping images to make them all the same size

[3]:
```
def crop_img(img):
    """
        Finds the exterior points on the image and crops to that limit
    """
    gray = cv2.cvtColor(img, cv2.COLOR_RGB2GRAY)
    gray = cv2.GaussianBlur(gray, (3,3),0)

    #Threshold the image + erode and increase size for better image

    thresh = cv2.threshold(gray,45,255, cv2.THRESH_BINARY)[1]
    thresh = cv2.erode(thresh, None, iterations = 2)
    thresh = cv2.dilate(thresh, None, iterations =2)
```

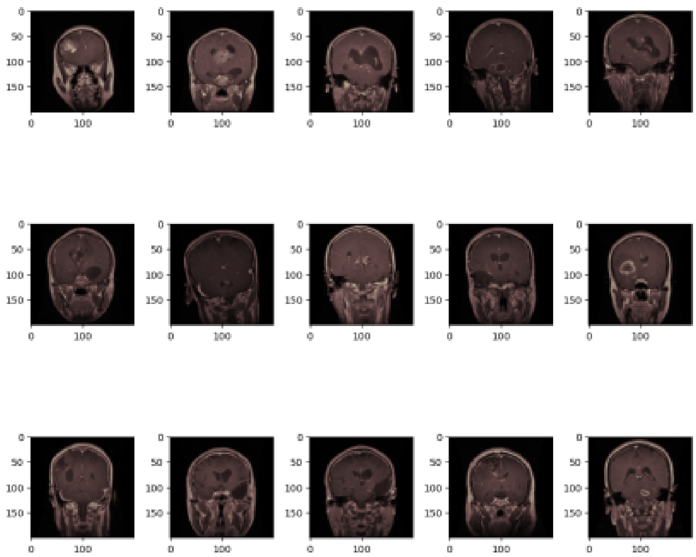
Figure 9.2: output 2



0.4 Cropping all the images

```
[16]: if __name__== '__main__':
        #training = "C:/Users/harsh/Downloads/capstone/Dataset/Train"
        training = "E:/SRM college/SEM-8/Dataset/Train"
        testing = "E:/SRM college/SEM-8/Dataset/Test"
        #testing = "C:/Users/harsh/Downloads/capstone/Dataset/Test"
        training_dir = os.listdir(training)
        testing_dir = os.listdir(testing)
        IMG_SIZE = 256

        ##Writing images for the training set

        for dir in training_dir:
            save_path = 'E:/SRM college/SEM-8/brain_tumors/cropped/Training/' + dir
            path = os.path.join(training,dir)
            image_dir = os.listdir(path)
            for img in image_dir:
                image = cv2.imread(os.path.join(path,img))
                new_img = crop_img(image)
                new_img = cv2.resize(new_img,(IMG_SIZE,IMG_SIZE))
                if not os.path.exists(save_path):
                    os.makedirs(save_path)
                cv2.imwrite(save_path+'/'+img, new_img)

        ## Writing images to the testing set
        for dir in testing_dir:
            save_path = 'E:/SRM college/SEM-8/brain_tumours/cropped/Testing/'+ dir
            path = os.path.join(testing,dir)
            image_dir = os.listdir(path)
            for img in image_dir:
                image = cv2.imread(os.path.join(path,img))
                new_img = crop_img(image)
                new_img = cv2.resize(new_img,(IMG_SIZE,IMG_SIZE))
```

Figure 9.3: output 3



0.5 Setting up the model

```
[6]: x_train, y_train = shuffle(x_train,y_train, random_state=42)

     y_train = tensorflow.keras.utils.to_categorical(y_train)
     y_test = tensorflow.keras.utils.to_categorical(y_test)

     x_train, x_val , y_train, y_val = train_test_split(x_train, y_train,
      test_size=0.2, random_state=42)

     print(x_val.shape)
```

```
(1143, 200, 200, 3)
```

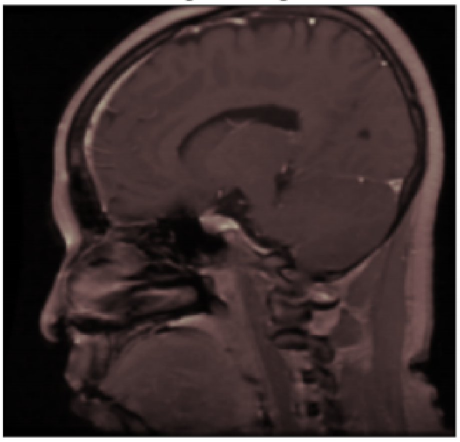
0.6 Actual Flipping of the images

- increased the parameters of change to ensure maximum accuracy

Figure 9.4: output 4

```
for img in os.listdir('preview_4/'):
    img = cv2.imread('preview_4/' + img)
    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    plt.subplot(3,7,i)
    plt.imshow(img)
    plt.xticks([])
    plt.yticks([])
    i += 1
    if i > 3*7:
        break
plt.suptitle('Augemented Images')
plt.show()
```

Original Image



```
<Figure size 1500x600 with 0 Axes>
```

```
[11]: datagen.fit(x_train)
```

##Using VGG instead of ResNet

```
[14]: # load base model
vgg16_weight_path = "E:/SRM college/SEM-8/
 ↪vgg16_weights_tf_dim_ordering_tf_kernels_notop.h5"
base_model = VGG16(
```

Figure 9.5: output 5

```
[12]: from keras.models import load_model
      vgg_model = load_model('h5_vgg_model.h5')
```

```
[21]: import pandas as pd
      history_frame = pd.DataFrame(history.history)
      history_frame.loc[:, ['loss','val_loss']].plot()
      history_frame.loc[:, ['accuracy','val_accuracy']].plot();
```

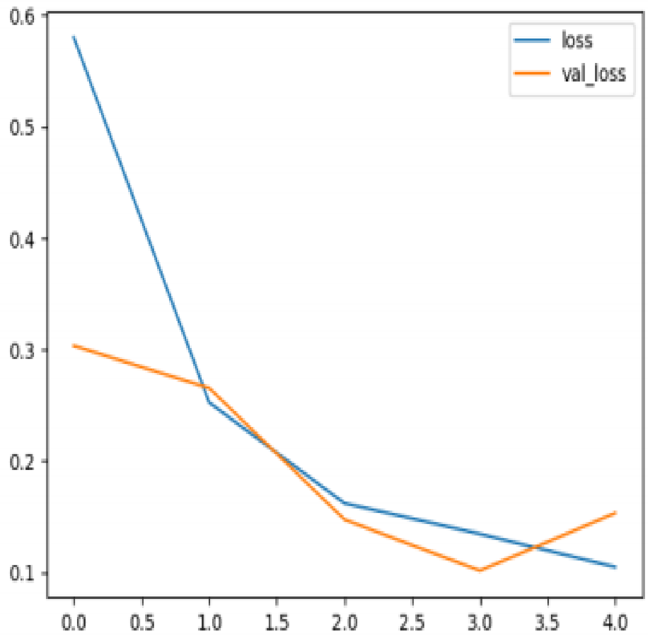
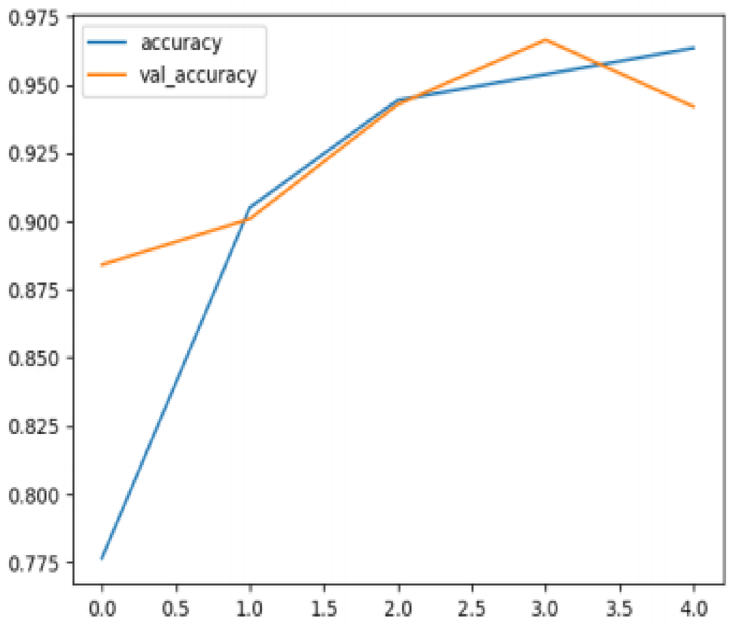


Figure 9.6: output 6



[13]:
```
pred = vgg_model.predict(x_test)

# Get the index of the maximum value along the second axis (axis=1)
pred_classes = np.argmax(pred, axis=1)

# Convert indices to class labels
pred_labels = [labels[i] for i in pred_classes]
```

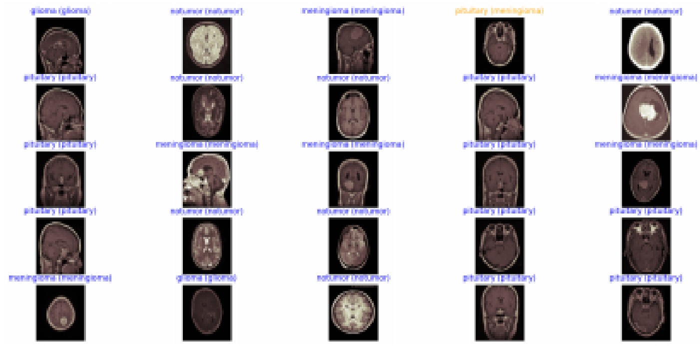
```
41/41 [==============================] - 153s 4s/step
```

[14]:
```
print(classification_report(np.argmax(y_test,axis=1),␣
↪pred_classes,target_names=['glioma','meningioma','notumor','pituitary']))
```

Figure 9.7: output 7

```
[19]: y_hat = loaded_vgg16_model.predict(x_test)

      # define text labels
      target_labels = ['glioma','meningioma','notumor','pituitary']

      # plot a random sample of test images, their predicted labels, and ground truth
      fig = plt.figure(figsize=(20, 8))
      for i, idx in enumerate(np.random.choice(x_test.shape[0], size=25,
       replace=False)):
          ax = fig.add_subplot(5,5, i+1, xticks=[], yticks=[])
          ax.imshow(np.squeeze(x_test[idx]))
          pred_idx = np.argmax(y_hat[idx])
          true_idx = np.argmax(y_test[idx])
          ax.set_title("{} ({})".format(target_labels[pred_idx],
       target_labels[true_idx]),
                       color=("blue" if pred_idx == true_idx else "orange"))
```

```
41/41 [==============================] - 161s 4s/step
```



0.7 Resnet101

```
[30]: early_stop_loss = EarlyStopping(monitor='loss', patience=2)
      early_stop_val_loss = EarlyStopping(monitor='val_loss', patience=2)
```

```
[32]: from tensorflow.keras.applications import ResNet101
```

Figure 9.8: output 8

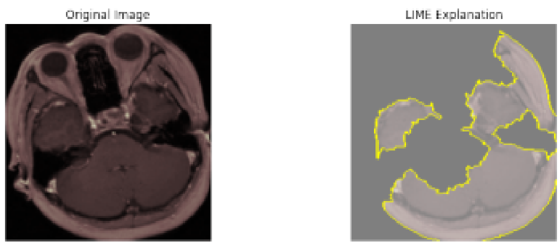
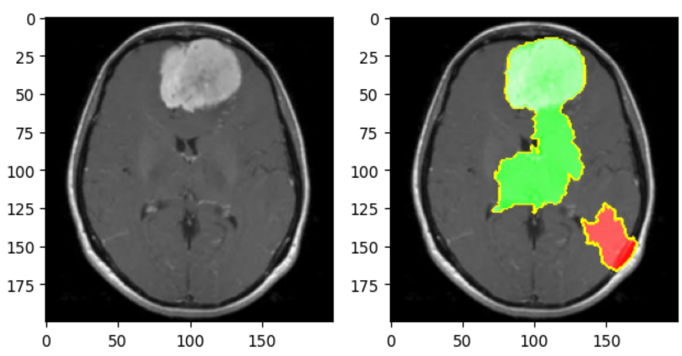


Figure 9.9: output 9

```python
import lime
from lime import lime_image
from skimage.segmentation import mark_boundaries

def xAI(model, img_dir):
    image = Image.open(img_dir)
    image = image.resize((200, 200))  # Resize the image to match the model's input shape
    main_img = image
    imgx = np.asarray(image)
    if len(imgx.shape) == 3:  # Check if the image is grayscale or RGB
        img = np.asarray(imgx[:, :, 0])
    else:
        img = np.asarray(imgx)
    img = img / 255
    img2 = np.zeros((np.array(img).shape[0], np.array(img).shape[1], 3))
    img2[:, :, 0] = img  # same value in each channel
    img2[:, :, 1] = img
    img2[:, :, 2] = img

    explainer = lime_image.LimeImageExplainer(random_state=42)

    # Define your labels
    labels = ["glioma", "meningioma", "notumor", "pituitary"]

    # Define a function to predict using your model
    def predict_fn(images):
        return model.predict(images)

    explanation = explainer.explain_instance(img2, predict_fn, labels=labels, top_labels=len(labels),
                                             hide_color=0, num_samples=1000)

    image, mask = explanation.get_image_and_mask(
        model.predict(img2.reshape((1, 200, 200, 3))).argmax(axis=1)[0],
        positive_only=False,
        hide_rest=False
    )

    plt.subplot(1, 2, 1)
    plt.imshow(main_img)
    plt.subplot(1, 2, 2)
    plt.imshow(mark_boundaries(image, mask))
    plt.tight_layout()
    plt.show()
```

Figure 9.10: output 10



<Figure size 640x480 with 0 Axes>

Figure 9.11: output 11

Chapter 10

CONCLUSION

To conclude, our research shows promise for deep learning to revolutionize brain cancers application of magnetic resonance imaging (MRI) for detection and classification We found advanced techniques in deep learning that could make models which were very precise at distinguishing and classifying between brain cancer cases. Instead of simply having exceptional diagnostic capabilities, they also gave invaluable understanding of diseases that help in the diagnosis as well as leading into more tailored and better treatment schemes. Our findings show how medical imaging is being transformed by deep learning with significant implications for improved patient care and clinical outcomes associated with brain tumor identification and management.

10.1 SCOPE OF FURTHER WORK

We are going to consider the strategies of group learning in a bid to enhance our models' accuracy and robustness when applied on different datasets and scenarios. In addition, we will explore how other Explainable AI (XAI) techniques can be integrated into them to gain a deeper comprehension of the behavior of the model and to clarify the reasoning behind the diagnostic findings. As such, we intend to create an easy-to-use web application which is customized for medical practitioners. This would enable seamless integration with clinical workflow. In this case, we would want to carry out comprehensive clinical trials to ascertain its functionality and performance under real-world conditions thus validating their effectiveness in real-life situations. I need to note that there are some shortcomings inherent in our present methodology such as dependence on limited size data set for training which reduces its applicability on new data sets. Moreover, highly accurate predictions require high-quality imaging since system's precision depends on MRI scans quality Nonetheless, accurate predictions depend upon high quality imaging because the precision of the system is based on the quality of MRI scans used However, our collaboration has made a major leap forward in the development of a credible, non-invasive approach to diagnosing brain tumors that potentially can revolutionize neuro-oncology clinical practice and improve patients' outcomes. The future seems bright in terms of upcoming studies on AR/VR applications for brain tumor detection and therapy. Another path for further researches could be building more interactive and immersive systems supporting real-time assistance to neuropathologists during operations with augmented reality. These advanced systems might rely upon AI algorithms as well as current imaging technologies so as to enhance tumor visualization, localization, resection accuracy. This will ultimately lead to improved surgical outcomes and enhanced patient safety." Besides, there is need for more research on VR simulations in surgical training."Yet" more investigations into the future may involve creating better VR platforms simulating realistic surgical conditions with haptic feedback technology reproducing tactile sensations thus offering students an authentic learning experience.

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