# Brain MRI Image segmentation using Deep learning techniques

MSc Research Project
Msc. in Data Analytics

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# Brain MRI Image segmentation using Deep learning techniques

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**Abstract**

It is the aim of this paper to find out how brain MRI image classification accuracy can be improved through a new hybrid deep learning model that incorporates Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), U-Net, ResNet, and GoogleNet. Given the importance of early detection of brain tumors for effective treatment, the new model was trained on a large dataset of brain MRI images resulting in a high validation accuracy of 97 percent. Despite this high performance, there were 20 misclassified images out of 600 indicating areas that could be tweaked. The research shows that integrating several advanced deep learning techniques greatly enhances tumor detection precision; it also reveals hybrid models' potential in medical image analysis.
**keywords**: Brain tumor, Hybrid Model, Gaussian Noise, CNN, U-NET, Google Net, External Validation,

## 1 Introduction

Rizwan et al. (2022) defined that BT is a condition that results from the uncontrolled bodily growth of cancerous cells within the cranial cavity. The brain is a confined organ with a fixed geometry and any mass that occupies that space can start affecting brain functions almost immediately, and also the chances of the tumor becoming malignant and invading other organs is high and fatal.
According to Sivadas and Ameer (2019) it is evident that brain tumors account for a 2 percent percentage of all human cancers. It is associated with relatively severe signs and outcomes. Most of them originate from the brain, although some of them are secondary, meaning a tumor in another part of the body has metastasized into the brain. They are further classified as malignant which are of high grade or benign which are of low grade. According to Khanmohammadi et al. (2023) pointed out that some tumors are benign in nature and; therefore, do not metastasize, while others are malignant in nature, and they grow rapidly, significantly impacting the brain, causing such things as emotional and physical problems. As stated by Rasool et al. (2022)state that doctors utilize scan composed of CT and MRI in order to identify tumors in the early stages. Klonisch et al. (2023) indicate that primary malignant brain tumors are especially perilous and that people diagnosed with them may die. According to Mostafa et al. (2023) Chemotherapy may be administered when the tumour is active, radiation therapy in some cases and surgery if the general health of the patient permits.

Research Question: How CNN, RNN, U-Net, ResNET, and GoogleNet deep learning techniques together are combined into a Hybrid model that can further improve the accuracy of Brain MRI images, and find whether it is a brain tumor or not?

Research objective: To develop a new architecture composed of CNN, RNN, U-Net, ResNet, and GoogleNet to increase the general performances of the brain tumor detection from MRI images. In addition, to avoid overfitting, during model building we will incorporate augmenting the inputs with Gaussian noise, dropout and L2 regularization. The same then shall be evaluated from external validation to ascertain accurate prediction in other datasets.

This research contributes to the extant literature in medical image analysis by creating a novel hybrid model aimed at identifying brain abnormalities. Thus in the disclosed work, along with the application of several state-of-art models, the study provides new strategies regarding accuracy and ways to handle problems associated with preprocessing and image format.

This Current research paper is structured in a way that section 2 is about reviews of literature review, its gaps followed by section 3 which is about research methodology. Then section 4 design specification comes into picture where architecture and algorithm has been discussed. In Section 5 implementation phases have been discussed, henceforth Section 6 where evaluation, results obtained, and discussion on various case studies have been mentioned. At last section 7 concludes the research paper with the ultimate findings and future work possibilities.

# 2 Related Work

In this related work section an analytic overview of brain tumor detection has been studied by doing an analysis of previous research papers and comparing those things with this current research paper and it has been divided into two parts subsection 2.1 and subsection 2.2.

## 2.1 Data Preprocessing and Data Augmentation

According to Mostafa et al. (2023) research, mainly focuses on some common types of data preprocessing like registration, resampling, and intensity standardization and some of the simple data augmentation techniques like geometric transformations. Compared to the current research, this paper provides a more diverse set of augmentation techniques that includes rotation, shear, zoom, flips, brightness, and channel shift – all intended to enhance the model's ability to generalize. Besides, it features data augmentation and the use of Gaussian noise to represent real-world fluctuations; or custom augment functions such as sharpening and edge detection. By supplementing the new techniques for learning, the gaps are closed as the model becomes stronger and more capable of handling the real-life situations that it will be faced with through the addition of noise and more superior augmentations.Sharma et al. (2022)research provides a strong method on how to perform data preprocessing and augmentation for the deep learning models' input based on normalization and other augmentations. Normalization is discussed in the study to keep the numerical range anchored enough and to fasten the training of deep learning models, concerning the first problem, changing the grey scale pixel values to a range between 0 and 255. As for augmentation, this research paper uses basic procedures like flipping (horizontal and vertical) and rotation (by 90 degrees) and brightness besides the intent of reducing the class imbalance by increasing the dataset. The use of these methods effectively contributes to enlarging the database from several hundreds of images to 1800 on average. However, the current research paper further builds upon these strategies of data augmentation by adopting more enhanced techniques that are Gaussian noise, channel shift, and other procedure such as sharpening and edge detection. These additions do not just enhance generalization capability but also supplement other realistic variations and stability; therefore, the above-mentioned flaws and variations of dataset and model about researchers' approach would be met.Rizwan et al. (2022) research involves pre-processing the CT scan images as a first step which involves down-sampling the images from a size of 512 x 512 x 1 to 128 x 128 x 1 pixels; the data is then split into training, validation and testing data with 35 percent of data used for validation and testing purposes while 65 percent of the data is used for training purposes. To reduce overfitting and increase model generalization, additional transformations including geometrical transformations and adding salt-pepper noise increase data to 15317 for type classification and 513 for grade classification. The current research paper continues from this study by applying further preprocessing, as well as a detailed data augmentation plan. These are such steps as resizing the images to 224*224 pixels and applying additional geometric and photometric distortions, such as flipping, rotation, scaling, Gaussian noise, etc. There are more variations in data through these enhancements while there are closer resemblances with real conditions; therefore, models become more accurate and strong as evident in sharp contrast to researchers' work.

## 2.2 Machine Learning Architecture, Model Choice, and Evaluation

Nawaz et al. (2022)The proposed HBTC framework applied to brain tumor detection has phases such as pre-processing the images, segmentation of images and tumor identification, feature extraction, and finally feature selection. They apply classifiers including MLP, J48, MB, and RT, with MLP being the most efficient. A new method adopted in this research enhances the HBTC structure by incorporating CNNs, RNNs, DenseNet, U-Net, and ResNet into the system. The previous model had some drawbacks which are then pointed and the actual model is improved on that aspect The accuracy together with ROC curves as well as confusion matrices are used in the assessment of the performance of the model. According to Işın et al. (2016) The research paper covers the automatic technique for the segmentation of brain tumors and the study is divided into discriminative as well as generative techniques for segmentation. Discriminative methods of feature-based models include classifier models such as neural networks, SVM, and random forests whereby, the models comprises of stages like preprocessing, feature extraction, and classification. Generative also creates statistics based on the properties of healthy tissue. More recent developments focus on deep learning, especially for CNNs for which the method automatically defines regions of interest by training from the images themselves. This paper aims at presenting a new model that integrates features of a CNN for feature extraction, an RNN for sequence processing, Dense Networks for classification, a U-Net for segmentation, and ResNet for classification improvement. This approach concern previous shortcoming such as high-dimensional data and feature selec-

tion problem and the performance is measured using metrics such as receiver operating characteristic (ROC) curves and the area under curve (AUC). It is clearly an improvement in the position that was formerly employed for mathematics, computer science, and tumor segmentation and classification.
The research by Mostafa et al. (2023) presents The deep learning method for the segmentation of the brain tumor in MRI scans proposed in this thesis is based on the improved U-Net model similar to that of the paper of Wang et al. with a validation accuracy of 98 percent. Nevertheless, in terms of segmentation, while it has limited relevance to real life. The current research aims to address this by using CNN, RNN, Dense Network, UNet, GoogleNet, and also ResNet models in order to improve the extracting of feature and flexibility. Hence, the paper concerns input dimensions for methodological advancement aimed at improvement of methods for model training, and their evaluation. The study by Sharma et al. (2022) proposes a new method to diagnose brain tumors through Transfer Learning with the use of the VGG19 CNN model, for segmentation. Classification got an accuracy of 98 percent for the model and a cross-entropy of 94 percent. It obtained 73 percent sensitivity in diagnosis which is higher than the existing approach. On this basis, the current research put forward a combination model. It improves the feature extraction and applicability of the method to the clinical application and there is a special emphasis on the input dimension corrections, training, and evaluation. This is done with the purpose of making the best clinically helpful application in assisting in diagnosis, and checking external data along with external image format whether it is a brain tumor or not. The survey done by Mlynarski et al. (2019) is unique because of the deep learning methodology used to find the extent of brain tumor and also to classify the tumor accurately. Their work stresses the implementation of a merging model that integrates CNNs together with the ordinary machine learning algorithms to encode the feature extractor and making it easier for the model to distinguish one type of tumor from another with higher efficiency. Nonetheless, this research has no solutions on how to tackle these issues at the clinical level or address the means through which these models are being operated. In extending the work done by Mlynarski et al. (2019) research paper, the current research creates a hybrid framework that not only adopts the merits of the multiple architectures for feature extraction as well as the classification. The proposed framework will be quite easy to link with the current existing clinical systems and should help in enhancing diagnostic capabilities as well as the outcomes of the patients. Therefore, the current study contributes to knowledge by overcoming the deficiencies that were identified with the previous studies and focuses on the real-world applicability of the findings.
The research of Rizwan et al. (2022) is devoted to machine learning for brain tumor detection; it applies deep learning approaches, specifically, CNNs for segmentation and classification. This paper illustrates the model as capable of distinguishing between the types of tumors present in the human brain and achieving near-perfect accuracy and sensitivity rates. The presented research explains how more efficient and accurate the authors' model is compared to previous approaches, but it largely stays at the level of algorithmic results and is not further translated into clinical practice at different stages of diagnostics. Therefore, this current research presents an advanced version of the hybrid framework that considers models which is not presented earlier by Rizwan et al. (2022). This new approach improves the procedures involved in feature extraction and classification since they adapt much better to real-world clinical data. While Rizwan's research mainly concentrated on algorithms, this study seeks to close the gap created by

the theoretical perspective and lack of practical application and testing of the existing models. To the same level of perceived usefulness, the proposed framework goes further to address the difficulties of integrating models like CNN, RNN, U-NET, GoogleNET, and ResNET in practice to provide superior solutions, also this current research paper is handling the validation of external data from the BRaTS2021 and STARAJ dataset which is missing in Rizwan's paper and that is why this proposed model is effective.Gu et al. (2021) The evaluation of the CDLLC method is done with metrics such as precision, and F1 score, combined with sensitivity analysis and optimization by grid search; however, this current research paper goes further by including highly complex deep learning architectures, and models that result in improved reliability and the ability to provide a more complete analysis of the model's performance. A literature review summary has been provided below:

In Table 1 a literature review summary has been provided.

Table 1: Literature Review Summary

| **Reference** | **Dataset** | **Technique Used** | **Accuracy** |
|---|---|---|---|
| Işın et al. (2016) | BraTS | SVM, AdaBoost, kNN, SOM, RF | 88% |
| Mostafa et al. (2023) | BraTS | CNN with Unet architecture | 98% |
| Sharma et al. (2022) | BraTS 2020 | Transfer learning with VGG19 | 98% |
| Mlynarski et al. (2019) | BraTS 2018 | CNN with ML classifier | 85% |
| Rizwan et al. (2022) | BT Dataset | CNN with segmentation | 98% |
| Gu et al. (2021) | BraTS | CDLLC, Precision, F1 and SA | 95.3% |

# 3 Methodology

Although numerous works have been done in regard to BT detection, the literature lacks comprehensive comparisons of various DL solutions and external validation as well. That is the reason why this work intends to identify and discuss some of the most suitable deep learning algorithms, which uses some methods combined them together into a hybrid model to predict brain tumor detection. In this research, the below figure Figure 1 will outline the process as proposed in the current research methodology.

## 3.1 Dataset

### 3.1.1 Training dataset

BR35H: According to the Naseer et al. (2021) paper the MRI scans used in the study pertaining to the detection of brain tumor are 255 without tumors and 255 with tumors on the BR35H dataset. These images are used 90 percent to train the system Its confidence level for this class is The confidence level of the system on this class Is This dataset contains both, T1 and T2 weighted MRI images. Consumer satisfaction and ease of use factors for the taxonomy are expressed in the value of the usability score which is reported as seven. 5, thus; licensing, tagging, data overview, description, simple usage, easy maintenance, machine readability, and metadata and public kernels.

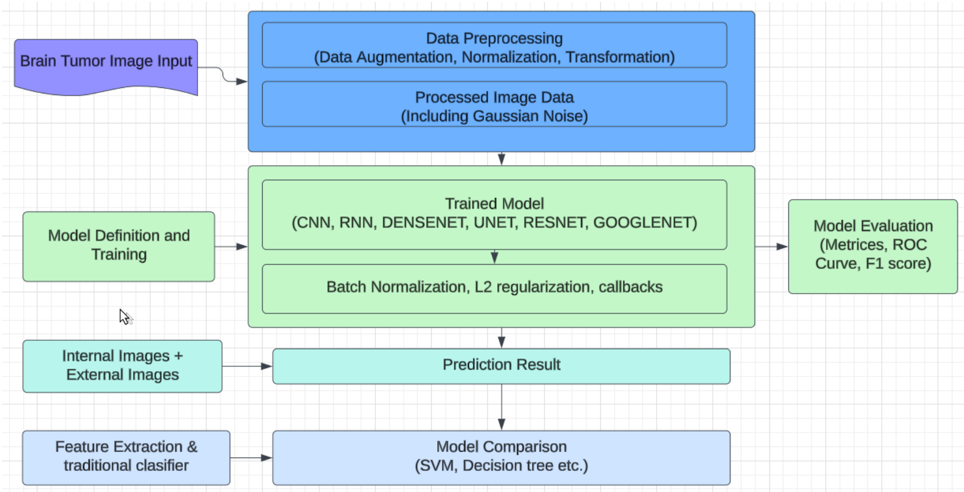


Figure 1: Research methodology

#### 3.1.2 Testing dataset

This dataset is a compilation of three sources: the SARTAJ dataset, BR35H, and BraTS2021 dataset. SARTAJ dataset includes a total of 7,023 human brain MRI images, which are categorized into four classes: A few of these machining types are glioma, meningioma, no tumor, and pituitary. The 'no tumor' class was obtained from the BR35H dataset to acquire samples of images.BraTS' dataset contains a large number of clinically diagnosed glioma patients' multi-parametric MRI scans with variable MGMT promoter methylation status. Since BraTS '20, the data sets allow for the evaluation of the accuracy of tumor segmentation predictions, as the datasets entail annotations of tumor sub-regions made by expert neuroradiologists.

### 3.2 Data Collection

In this research, the given dataset consists of images in two main folders, namely 'yes' and 'no' which depict brain-scanned images with and without tumors, respectively. Even these images are arranged in a folder structure where the 'yes' folder contains brain scan images with tumors and the 'no' folder with the images without tumors. It also has different types of images and image sizes; all of these images go through data preparation and resizing so that they acquire the standardized size of 224 x 224 pixels. Data Collection sample and ratio Figure 2

### 3.3 Data Preprocessing

In this section first comes the image preprocessing step in which images are first read in raw format and then resized to have the dimension of 224×224 pixels using the PIL library. Such resizing has the capability of making all the input images have an equal spatial requirement so that they can fit in the neural network models batch processing. Some samples are being shown in Figure 3

After resizing, bilateral filter kernel and the image pixel intensity values are scaled to

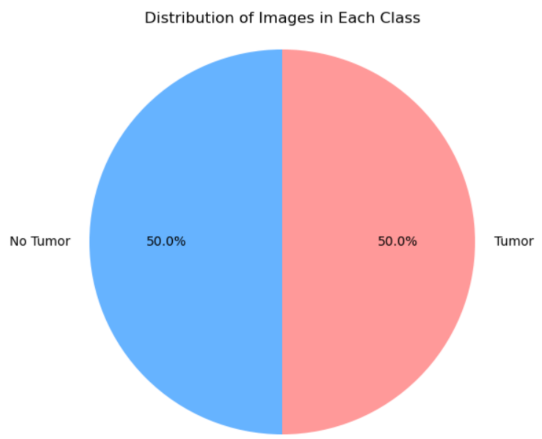


Figure 2: Distribution of images in class

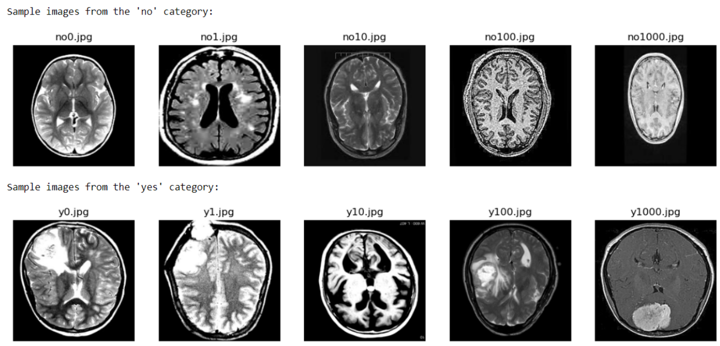


Figure 3: Before Data Augmentation

a range of 0 to 1. This normalization is done by bringing all the pixel values in the same range with the aim of eliminating the large value effect by dividing them by 255. 0 which is useful to keep the numerical stability during the training phases and further guarantee the input data are in the range of learnability for the neural network.

## 3.4 Data Augmentation

Data augmentation is a technique applied to increase the variability and the stability of the training sets especially when considering to brain tumor detection. In this research, the following data augmentation techniques were employed with a view of increasing the effective size of the training data and its diversity.

Random values of rotation included in the range of $\pm 15$ degrees were applied to meet the criterion of articles' randomness. A strategy used in this technique assists the model in diminishing rotation consistency in the images. Because tumors are also detected in the scans at different positions, rotation means that the model can recognize them from any angle. Also, the width and height shifts were used, which changed the location of images either horizontally by shifting them by up to 10 percentage of the image's width, or vertically.

Shear transformations were also employed to turn by plus/ minus 20 percent the view of the images. Another augmentation was zooming of plus/ minus 20 percent which controls the size of the captured images.To increase the level of robustness even more, the technique of horizontal and vertical flip operations was applied. Brightness changes were also made, and the tested image brightness was increased to between 80 and 120 percent of the original's brightness. This technique familiarises the model with the different lighting conditions that may arise because of differences in the scanning equipment or the patient position. Figure 4 is sample images after the Data Augmentation

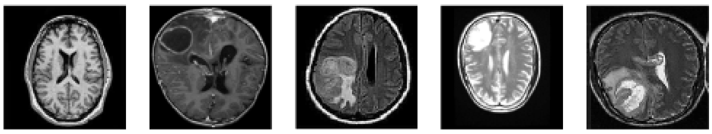

Figure 4: After Data Augmentation

The noise in the form of Random Gaussian having an average of 0 while the standard deviation was evaluated to be 0. This addition imitates the kind of noise that which is usually existed in the images and it sets the model for such variation. These augmentations were initiated by TensorFlow's 'ImageDataGenerator' and can be easily incorporated during the training because the real training occurred on slightly altered versions of the images in each epoch which has been shown in Figure 5.

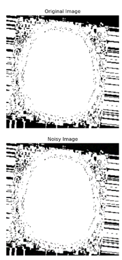


Figure 5: Gaussian Noise

## 3.5 Model Architecture

To expertly handle brain tumor classification, the researchers have employed multiple parts that distinguish the architecture of a model. The main model is a custom Convolutional Neural Network (CNN) with such layers as convolutional layers for feature extraction and max pooling layers for dimensionality reduction. This CNN has been created to discover fine-grained patterns and features in images. A hybrid model architecture has also been developed where different models are combined for better performance by capitalizing on their individual advantages. These include combinations of CNNs, Recurrent Neural Network (RNN) layers for sequence processing, and Dense networks for powerful classification. Additionally, pre-trained models like ResNet, GoogleNet, and U-Net have been embedded into the architecture to make use of their strengths in feature extraction and segmentation respectively.

## 3.6 Training Process

The model's training process is geared towards effective learning and performance optimization. The model is trained with both the train and validation datasets, adjusting the model parameters in order to minimize loss and maximize accuracy. It involves setting up appropriate hyperparameters such as batch size, learning rate, number of epochs that will help balance between training time and model performance. To achieve this, an optimizer like Adam or some other related ones are used which enables adaptive change of learning rates thereby promoting convergence. Various approaches such as early stopping and reducing the rate of learning have been employed to curb overfitting and increase generalization.

## 3.7 Evaluation

The evaluation method comprises of assessing how accurately the model performs with unseen test data and its generalizability. Accuracy, precision, recall and F1 score are some of the key metrics that can be computed.

# 4 Design Specification

The design specification of the hybrid architecture is intended to combine enable strengths of multiple neural networks models for comprehensive brain tumor MRI analysis. A combined approach of Convolutional Neural Networks (CNNs), RNN, U-Net, Residual Networks (ResNet), GoogleNet, and Dense Connection Networks has been widely used in this system to be able to process MRI images accurately for the detection of brain tumors. Each of these elements is hand-picked mainly because they can excel in feature extraction, segmentation, and pattern representation selected together with an improvement that contributes to performance accuracy in terms of efficient computing.

## 4.1 Architectural Overview

### 4.1.1 CNN

The CNN module plays a crucial role in extracting top-level attributes from MRI pictures. Convolutional operations are used for spotting spatial hierarchies and patterns in the images. CNNs are best at capturing fine-grained features such as edges, textures, and shapes which are important for tumor identification and classification.

### 4.1.2 U-Net

U-Net has become a household name in the context of segmentation, as it is designed for the exact delineation of images. The architecture that involves an encoder-decoder with skip connections can model both high-level and fine-grained spatial properties. In the case of MRI images, it accurately segment tumor which is important because it not only helps determine whether a tumor exists but also with more information such as the area of the border where segmentation needs to be performed accurately.Below figure Figure 7 U-Net architecture sample diagram

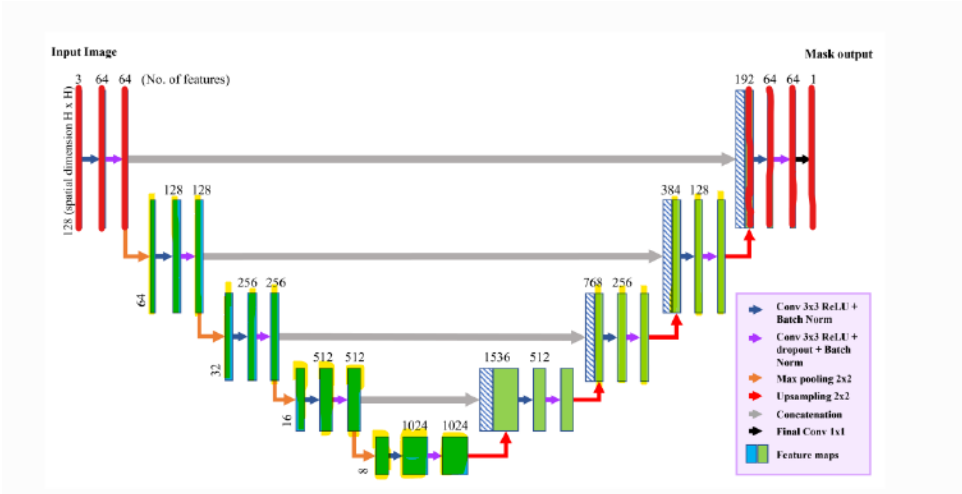


Figure 6: Gupta et al. (2023) U-Net Diagram for Brain tumor detection

### 4.1.3 RNN

RNN can be quite useful if the MRI data has been presented in a sequence or is temporal. RNNs are useful when analyzing a sequence of MRI scans over time or slices from an MR scan that can be considered as representing a sequence. Temporal dependencies and changes, such as the progression or variations of a tumor are analyzed well by RNNs.

### 4.1.4 ResNet

According to He et al. (2015) ResNet utilizes deep residual learning with residual blocks, which essentially enables a network to successfully train extremely deep architectures.ResNet is good at extracting fine-grained features/patterns due to its inherently deep nature and deal with complexity like variability in the appearance or shape or size of medical images. Thus, it facilitates higher final classification accuracy. The below image Figure **??** is the ResNet architecture example

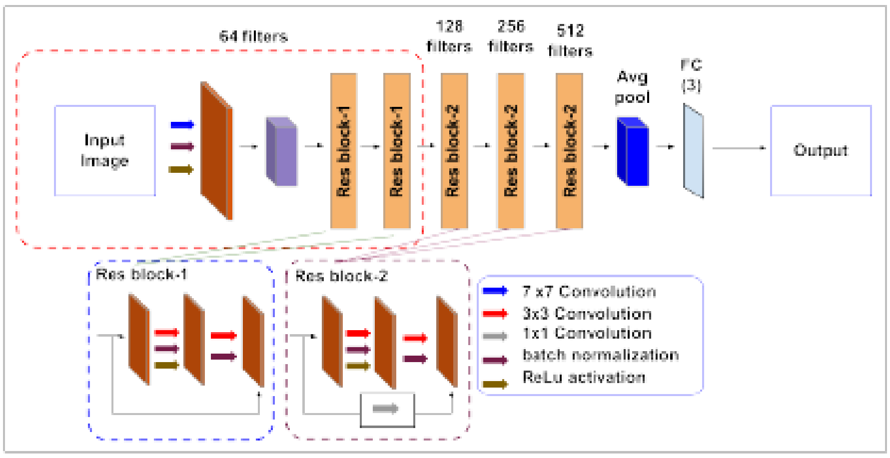


Figure 7: Saifullah and Drezewski (2024) ResNet Architecture for brain tumor detection

### 4.1.5 DenseNet

DenseNet encourages feature propagation and reusing by connecting each layer to all preceding layers. This encourages feature reuse, reduces model redundancy, and thus helps in optimization. For the MRI image analysis task, DenseNet has the potential advantage of integrating features from different stages for better and more insightful feature representation learning. Thus it can yield a powerful model capability that learns complex hierarchy pattern information with improved classification performance. Figure 8 is the example of a dense network

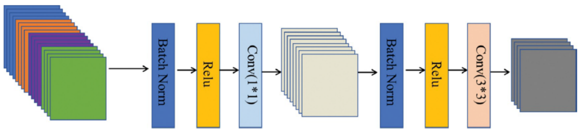


Figure 8: Dense Block

### 4.1.6 GoogleNet

In the context of identifying brain tumors, the valuable features of MRI images must be successfully extracted by using GoogleNet which can be referred to as InceptionV3. It carries forward post-processing from ImageNet for detecting intricate patterns in the MRI scans of the brain. This generally involves using features from InceptionV3 together with from other models in a manner referred to as a hybrid system. This makes it easier for the model to discern what is likely to be a tumor and what is not. So, by using InceptionV3 as a feature extractor and fine-tuning it for this type of task, the model's performance and its ability to classify the images correctly increases.

## 4.2 Techniques used and their impact

### 4.2.1 Integration of Diverse Model

The hybrid architecture contains CNN, U-Net, ResNet, DenseNet, GoogleNet, and RNNs. CNN applies effective spatially localized information extraction to magnetic resonance images to identify patterns in the brain. U-Net allows the high-resolution marking of an object boundary through its perfect design. ResNet enables a neuron network model with increased depth and stronger featuring capability using its residual learning method. DenseNet enhances the interconnection between layers by enhancing the capabilities of feature reuse within a network. RNNs can contribute in terms of the perfection of diagnosis and prognosis of MRIs by integrating temporal data during analysis.GoogleNet uses an inception module that uses global average pooling to efficiently capture the multi scaling feature.

### 4.2.2 Batch Normalization

Batch normalization is employed to normalize activations within the CNN layers, which stabilizes getting to know and accelerates the education manner.In the context of mind tumor MRI pics, batch normalization stabilizes the education process, ensuring powerful getting-to-know and generalization regardless of the complicated features present in clinical data.

### 4.2.3 Transfer Learning

The version uses ResNet50 with weights pre-trained on ImageNet, which offers a solid base for extracting features. Transfer learning takes the gain of knowledge gained from a massive, various dataset, which is beneficial when operating with smaller MRI datasets. Fine-tuning customizes those capabilities to boost accuracy and improve the detection of brain tumors.

### 4.2.4 Regularization

To avoid overfitting, the model uses regularization techniques like L2 regularization and dropout. L2 regularization helps prevent overfitting by penalizing large weights in Dense layers. Dropout is applied before the final classification layer to randomly ignore some neurons during training, which also helps reduce overfitting.

### 4.2.5 Learning Rate

The LearningRateScheduler modifications the studying fee depending at the epoch, which enables the model educate more efficaciously. For complicated MRI images, adjusting the learning fee for the duration of education allows the version to do better performance tuning, leading to higher tumor prediction.

### 4.2.6 Callbacks

Several callbacks are used to enhance schooling and model overall performance. EarlyStopping stops training while the validation loss stops enhancing, preventing overfitting. ReduceLROnPlateau lowers the gaining knowledge of fee whilst the validation loss ranges off, supporting the version to train extra successfully. ModelCheckpoint saves the version with the exceptional validation loss, so the exceptional version is stored.

# 5 Implementation

The implementation of brain tumor detection from MRI images has gone through several steps:

## 5.1 First Step of the implementation phase

To obtain the brain scan images belonging to the chosen dataset which is followed by applying different types of data augmentation to the obtained images.The dataset is divided into a training set and a test set in the ratio of 8:2. All images are resized to the input dimensions of 224 x 224. Any image is preprocessed by changing the range of pixel values by dividing the values by 255. The shape of the training data turns out to be (num_train_samples, 224, 224, 3); on the same note, the shape of the testing data is (num_test_samples, 224, 224, 3). Labels are one-hot encoded so we get an array with the shape of (num_samples, 2) for binary classification.

## 5.2 Second Step of the implementation phase

Different architectures are incorporated into the hybrid model to optimize the various architectural characteristics. For CNN (Convolutional Neural Network) components, the architecture is initiated with an input layer that takes images of the size 224x224x3. The convolution layers are a Conv2D layer with 32 filters and a kernel of 3X3 pixels, with ReLU activation; another Conv2D layer with 64 filters and a kernel of 3X3 pixels also with ReLU activation. A MaxPooling2D layer with a pool size of 2 is used; one added Conv2D layer with 32 filters embedded followed by another MaxPooling2D layer with a pool size of 2. The Flattening Layer reshapes the 2D feature maps to 1D vectors; Dense layers with 128 units and ReLU activation; then a Dropout layer of 0. Be placed before the second hidden layer, which is an Output Dense layer comprising of two units and a softmax activation function, The dropout layers were implemented with a dropout rate of 5 percent. The constituents of an RNN are an Input Layer for sequences, LSTM layers for time dependencies, and further Dense layers. Numerical data is fed through the Dense Network component in which there are several connected layers. UNet is especially used for segmentation, It has an Encoder Path of Conv2D and MaxPooling2D layers, a Bottleneck has intermediate layers and a Decoder Path of up-sampling layers, and the last Conv2D for the segmentation. ResNet50 uses transferred weights and consists of residual blocks of two 3 x 3 convolutions, a 1x1 convolution layer for dimensionality reduction, and the Global Average Pooling layer. A model that is built on the pre-trained weights is InceptionV3 that contains Inception Modules that consists parallel Convolutional Layers and Pooling Operations, Reduction Layers to downsample the feature map, and Global Average Pooling for the Classification.

## 5.3 Third Step of the implementation phase

The implemented hybrid model is also used for evaluating the effectiveness and also determine the accuracy of the training set as well as the accuracy of the test set. A Classification Report provides precision, recall, and the F1 score of the packing classifier along with other classes. The confusion matrix which provides a clear picture of the ML model along with the true classes and predicted classes is depicted in the heatmap. ROC Curves and AUC Scores of stability between the classes provide ROC diagrams for every class and the calculated AUC.Feature extraction is therefore the extraction of the intermediate outputs from the layers of the mentioned hybrid model and can be used in other subsequent procedures. The obtained feature representations are then used as the input to standard classifiers. Support Vector Machine linear kernel, Decision Tree classifier basic, basic K-Nearest Neighbors with $K = 2$, basic Random Forest, and Logistic regression with Iteration = 1000 for model estimation.

# 6 Evaluation

In this current research, model evaluation has been done in the form of some specific parameters like confusion matrix, Training and Validation accuracy over epochs, ROC Curve for each class, and actual vs predicted labels.

1. Confusion Matrix: In Figure Figure 9 confusion matrix which is Concerning class 0, as well as class 1, Precision, Recall, and F1-score, are all equal to 0.97, which shows

that performance is superb and well-balanced in the offered criteria. The support values show that the number of instances for class 0 is 313, while for class 1 there are 287 instances, what can be considered as quite balanced.

```
19/19 [==============================] - 110s 5s/step
Validation Accuracy = 0.97
Classification Report:
              precision    recall  f1-score   support

           0       0.97      0.97      0.97       313
           1       0.97      0.97      0.97       287

    accuracy                           0.97       600
   macro avg       0.97      0.97      0.97       600
weighted avg       0.97      0.97      0.97       600
```

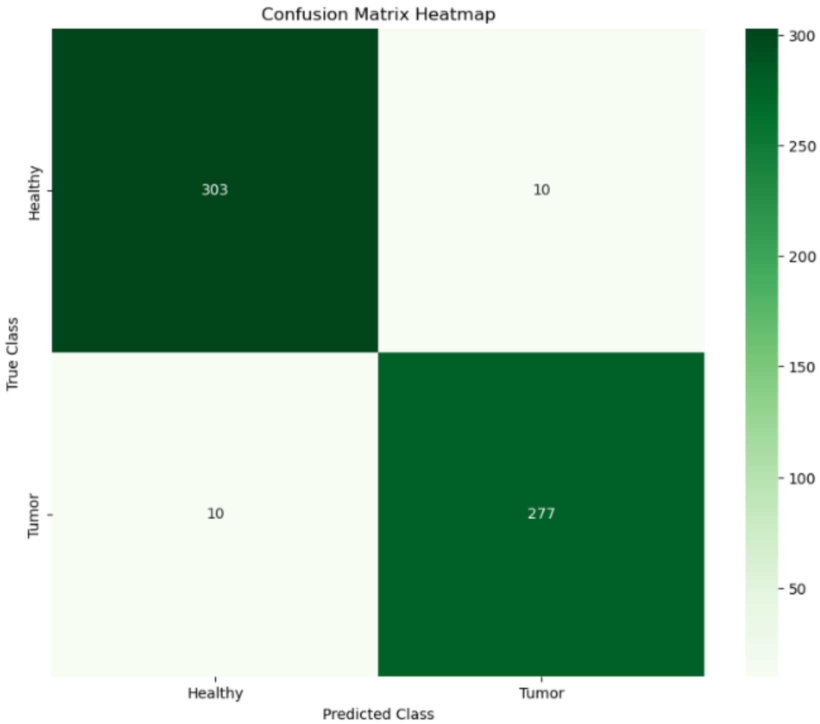


Figure 9: Confusion Matrix

2. Training and validation accuracy over epochs: The figure Figure 10 depicts the exact percentage of accuracy of the model on its training and validation data set against the epochs. It features two lines: blue to represent training accuracy and red to represent validation accuracy and the graph can be created concerning epochs. It also becomes easier to observe the value on the Y-axis, which starts from 0.75 to 0.95. This plot assists in determining how well the model is learning and how well it generalizes over time.

3. ROC Curve for each class: This diagram Figure 11 involves ROC curves for the two classes: Class 0 (AUC = 0. 99) and Class 1 (AUC = 0.99); the axes of the curves, false positive, and true positive are used. An AUC of 0.99 for both Class 0 and Class 1 shows that the model performs exceptionally well and its discriminatory ability between the classes is high. But to eliminate any possibility of an overfitting scenario, this result needs to be verified by using other datasets on a hold-out basis and comparing it to basic models.

4. Actual vs predicted labels for test images: from Figure Figure 12 it has been seen that

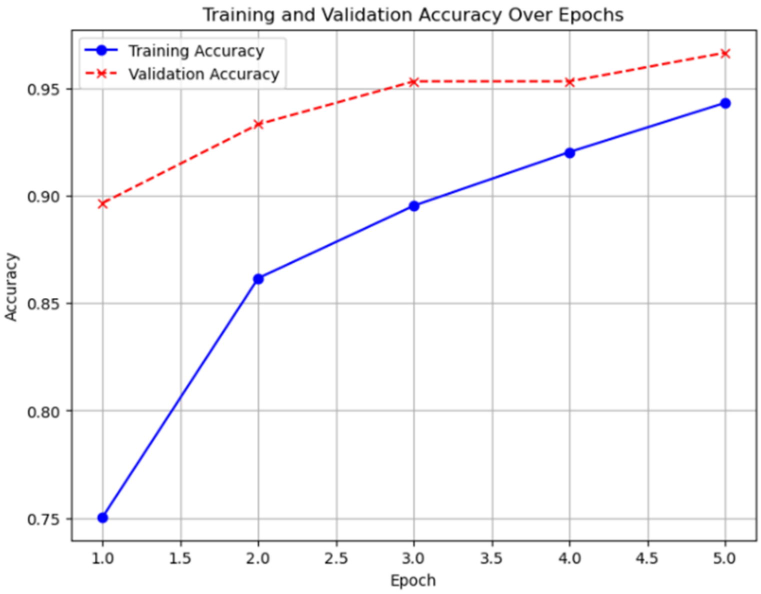


Figure 10: Training and Validation accuracy over epochs

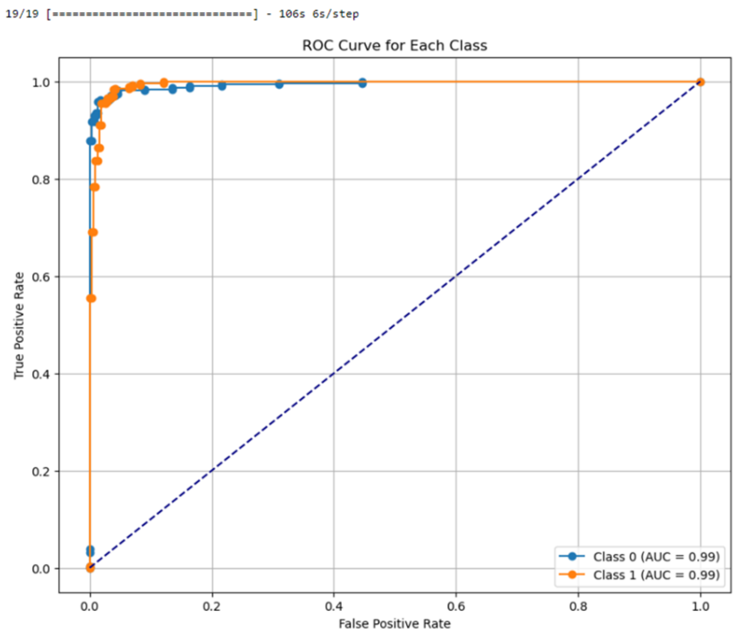


Figure 11: ROC Curve for each class

the grid contains brain scans or MRI images with true and predicted classifications, By marking the images with actual and predicted labels.

## 6.1 Positive Case Study

### 6.1.1 Input Tumor Images from BR35H Dataset

After giving a Tumor image from the BR35H dataset it predicts correctly in Figure 13.

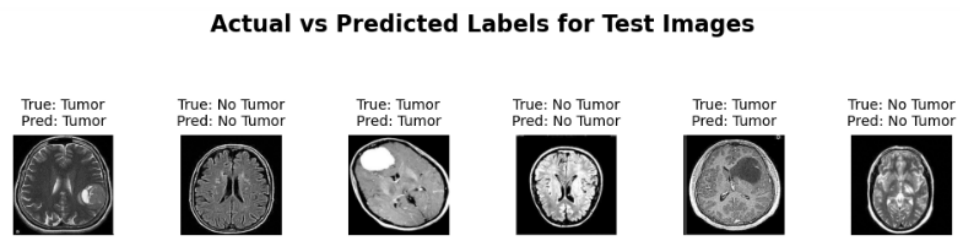


Figure 12: Actual vs predicted labels

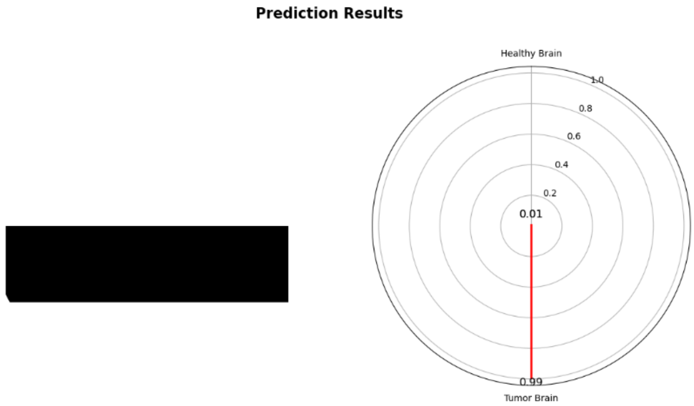


Figure 13: Tumor image from the BR35H dataset predicts correctly

### 6.1.2 Input No-Tumor Images from BR35H Dataset

After giving a No-Tumor image from the BR35H dataset it predicts correctly in Figure 14.

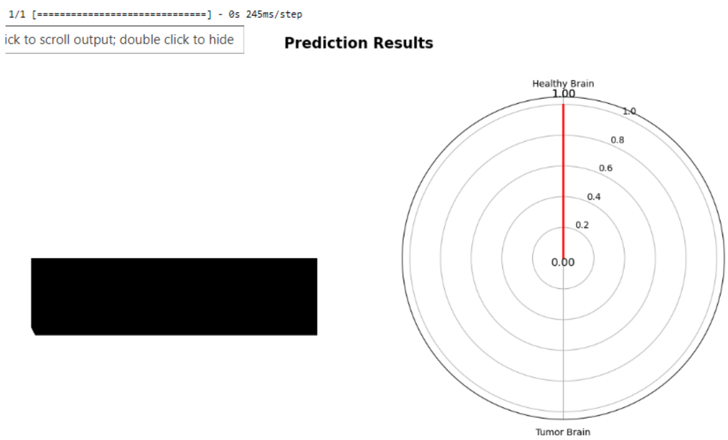


Figure 14: No-Tumor image from the BR35H dataset predicts correctly

### 6.1.3 Input External Tumor Image(Meningioma) from SATRAJ Dataset

After giving a meningioma tumor image from the SATRAJ dataset it predicts correctly in Figure 15.

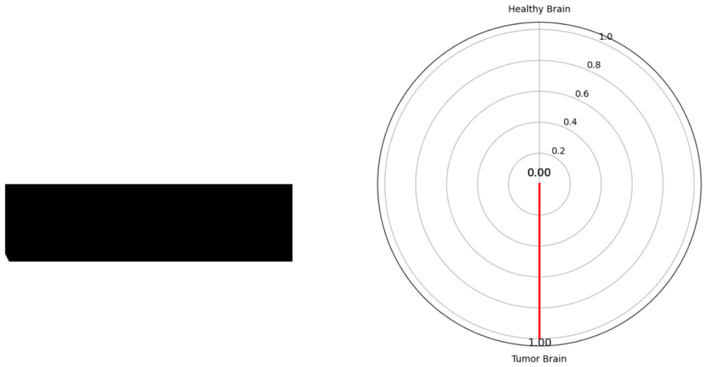


Figure 15: meningioma tumor image from the SATRAJ(External) dataset it predicts correctly

### 6.1.4 Input External Tumor Image(Pituitary) from SATRAJ Dataset

After giving a pituitary tumor image from the SATRAJ dataset it predicts correctly in Figure 16.

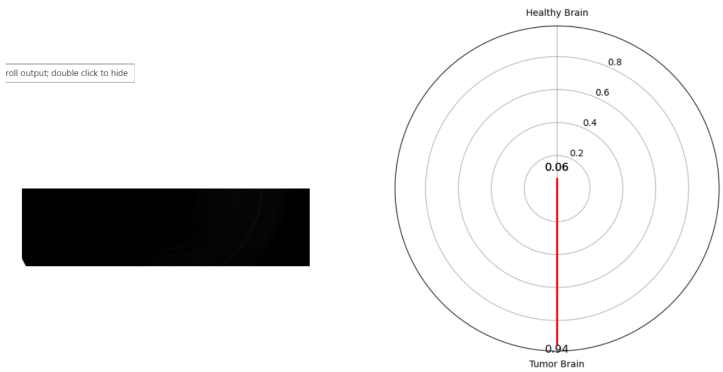


Figure 16: pituitary tumor image from the SATRAJ(External) dataset it predicts correctly

### 6.1.5 Input External Tumor Image(Glioma) from SATRAJ Dataset

After giving a Glioma tumor image from the SATRAJ dataset it predicts correctly in Figure 17.

### 6.1.6 Input External no-tumor from SATRAJ Dataset

After giving a no-tumor image from the SATRAJ dataset it predicts correctly in Figure 18.

### 6.1.7 Input External no-tumor from BraTS2021 Dataset

After giving a no-tumor image from the BraTS2021 dataset it predicts correctly in Figure 19

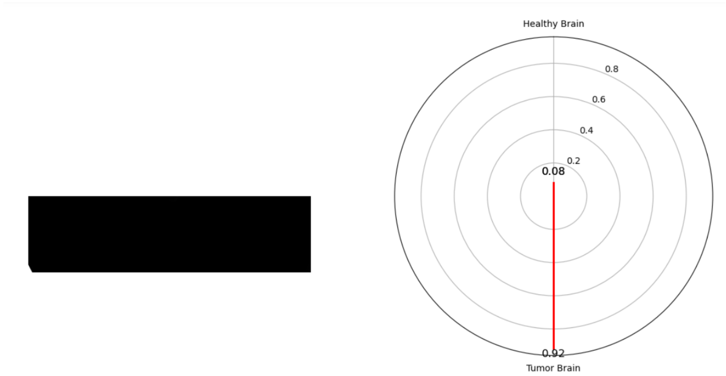


Figure 17: Glioma tumor image from the SATRAJ(External) dataset it predicts correctly

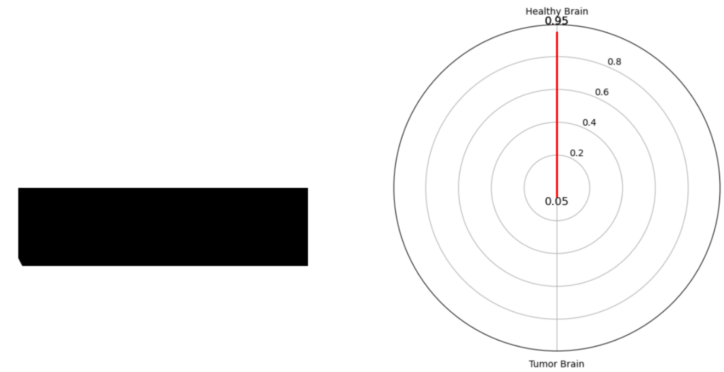


Figure 18: No-Tumor image from the SATRAJ(External) dataset it predicts correctly

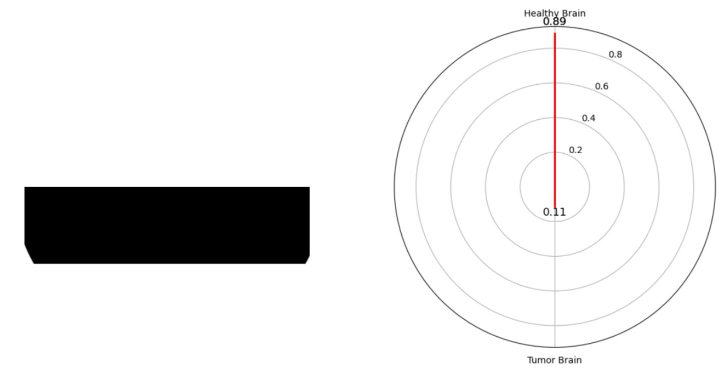


Figure 19: No-Tumor image from the BraTS2021(External) dataset it predicts correctly

## 6.2 Negative Case Study

### 6.2.1 Input External tumor Image(Glioma) from SATRAJ Dataset

Figure 20 shows 73 percent brain tumor and 27 percent healthy brain for SATRAJ(glioma).

### 6.2.2 Input External tumor Image(Glioma) from SATRAJ Dataset

Figure 21 shows 39 percent brain tumor and 61 percent healthy brain for SATRAJ(glioma).

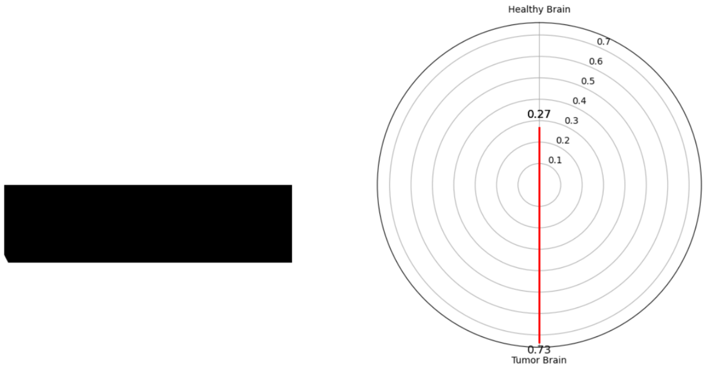


Figure 20: Glioma Tumor SATRAJ(External) shows 73 percent brain tumor and 27 percent healthy brain

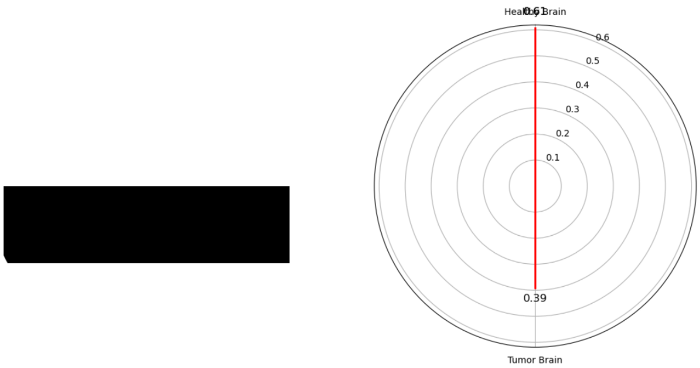


Figure 21: Glioma Tumor SATRAJ(External) shows 39 percent brain tumor and 61 percent healthy brain

## 6.3 Discussion

From the result, the hybrid model proves to have a very good performance whereby, out of 600 images, 580 are correctly classified thus giving it an accuracy of 97 percent. Still, 20 images raise issues. Key findings include:

1. In the construction of the SATRAJ dataset especially for glioma images, both malignant and benign tumors are present which may influence prediction.

2. Some steps of the image preprocessing and augmentation should be improved.

3. Modeling limitations: Overfitting might be exactly of high degree that spoil the prediction accuracy of the model.

4. Things such as equations, structures, and function transformations that the model only supports .jpg and, .NII formats, which resulted to other formats failure.

5. A test with external data gives the level of accuracy between 65-70 percent, so, further training is required with more various sets.

Optimizing the methods of preprocessing, augmenting, and normalizing the data, and widening the list of supported image formats may improve the result of meshing.

# 7 Conclusion and Future Work

The study aims at investigating the possibility of enhancing the level of accuracy in the classification of brain MRI images for the detection of tumors by enlightening a hybrid model formed through the integration of CNN, RNN, U-Net, ResNet, and GoogleNet. The model had a good validation accuracy of 97 percent which pointed to high output. Moreover, the results demonstrated that 20 images out of the 600 were incorrectly classified. In this research, the incorporation of various deep learning approaches proves to be effective in the detection of brain tumors with high levels of accuracy, even though there are issues that may relate to the classification effectiveness or compatibility of the images.

The classification ability of the proposed model that consists of CNN, RNN, DenseNet, U-net, ResNet, and GoogleNet on 600 test images is impressive where it accurately controlled 580 images out of the test 600 images. Nonetheless, even 20 images can be referred to as problematic, even under the auspices of the indicated success. Future work should focus on several areas: streamlining the mechanisms of input image pre-processing and data augmentation, dealing with the possible issue of overfitting through the application of dropout and other approaches, as well as other architectural changes that can enhance the model's accuracy. It is also crucial to note that the model's capacity to provide formal support for rendering from one to another of formats different kinds of images also requires enhancement; additionally, it is necessary to incorporate a rich set of various data for external testing. Moreover, the fine-tuning of the given model can be done and it can be known by following Advanced Data Augmentation, Full Hyper-parameter Tuning, Online Testing of Machine Learning Model. Next tasks of the work include explaining the model, which will be performed by studying and applying the filter methods that help remove features, which are not critical for the results and by pruning to reduce the concepts and increasing its reliability and inter benches' credibility.

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