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Brain Tumor Detection and Localization: An Inception V3 - Based Classification Followed By RESUNET-Based Segmentation Approach

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Abstract
Adults and children alike are at risk from brain tumors. Accurate and prompt detection, on the other hand, can save lives. This research focuses on the identification and localization of brain tumors. Many research has been available on the analysis and classification of brain tumors, but only a few have addressed the issue of feature engineering. To address the difficulties of manual diagnostics and traditional feature-engineering procedures, new methods are required. To reliably segment and identify brain tumors, an automated diagnostic method is required. While progress is being made, automated brain tumor diagnosis still confront hurdles such as low accuracy and a high rate of false-positive outcomes. Deep learning is used to analyse brain tumors in the model described in this work, which improves classification and segmentation. Using Inception-V3 and RESUNET, deep learning is pragmatic for tumor classification and segmentation. On the Inception V3 model, add one extra layer as a head for classifying. The outcomes of these procedures are compared to those of existing methods. The test accuracy of the Inception-V3 with extra classification layer model is 0.9996, while the loss value is 0.0025. The model tversky value for localization and detection is 0.9688, while the model accuracy is 0.9700.

Keywords- Brain tumor, Classification, Segmentation, MRI, Inception V3, RESUNET, Deep learning.

1. Introduction

The brain is the large, intricate part of the human body that controls the nervous system as a whole and contains around 100 billion nerve cells (Louis et al., 2016). The genesis of this vital organ lies at the neurological system's core. Because of this, every abnormality in the cortex has the possibility of putting the health of the public in peril. The most severe of these conditions have been brain tumors. Brain tumors are two distinct types of uncontrolled, aberrant cell growth in the neurological system: primary tumors and malignant tumors. Malignancies migrate through the bloodstream from numerous different components of the human body to the extracellular space, whereas primary tumors are detected in the brain parenchyma (Tandel et al., 2019). Glioblastoma and meningioma are two dangerous forms of brain tumors that can kill a patient if not caught early enough (Anaraki et al., 2019). Glioblastoma is the most frequent kind of brain tumor in humans (Kang et al., 2021).

Brain tumors are divided into four classes (Figure 1) by the World Health Organization (WHO) (Louis et al., 2016). Lower-level tumors (e.g., meningioma) are classified as grade 1 and 2, whereas more severe tumors are classified as grade 3 and 4. (e.g., glioma) (Rao and Karunakara, 2021). Glioblastoma, pituitary, and Meningioma tumors have incidence rates of 45 percent, 15 percent, and 15 percent, respectively, in clinical practice.

Medical knowledge is extremely substantial as a result of significant advancements in medical image collecting technologies that contain a variety of sense modality and procedures, such as Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI), and, Computed Tomography (CT), among others. Doctors may do quantitative evaluations of brain tumors such as the volume, diameter, and maximum quantity of brain lesions with the use of complete information and multimodal MRI brain imaging, allowing them to build a diagnosis and the best treatment plan for their patients. This study uses a variety of magnetic resonance imaging (MRI) pattern images for the diagnosis, including T2-weighted MRI, T1-weighted MRI, proton density-weighted MRI, and fluid-attenuated inversion recovery-weighted MRI. Early detection of brain tumors is crucial for effective treatment. After a brain tumor is clinically suspected, radiological evaluation is required to determine its location, size, and impact on the nearby areas. This data is used to determine the best course of treatment, which may include surgery, radiation therapy, or chemotherapy. It appears that the patient's chance of survival can be significantly increased if the tumor is correctly detected at an early stage.

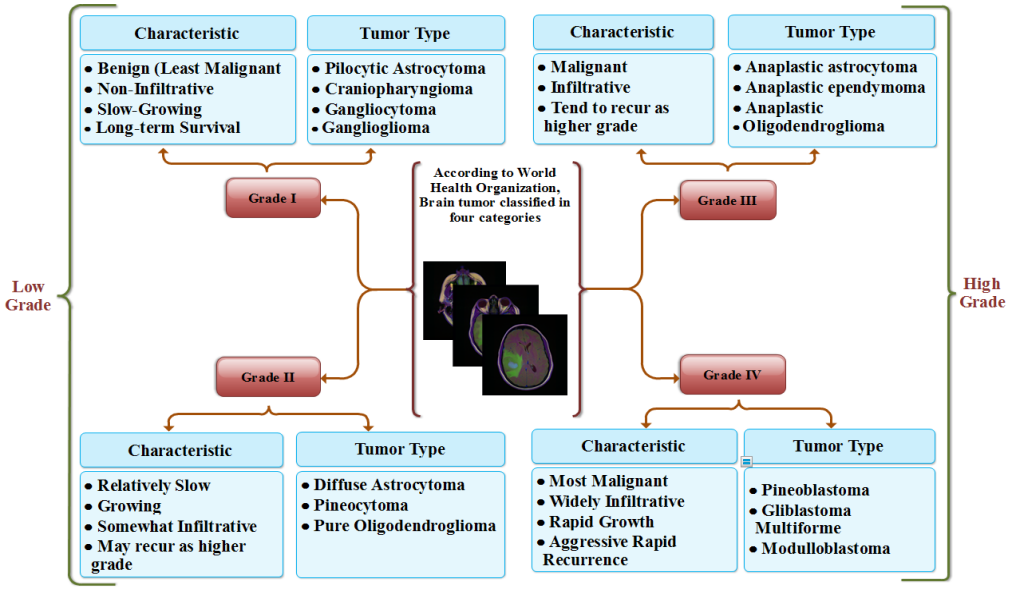

Figure 1. WHO Grade for brain tumor.

Radiologists must manually segment tumors, which is a difficult, error-prone, and time-consuming procedure since tumorous and non-tumorous cells seem to be identical (Latif et al., 2021). Furthermore, it has been discovered that the tumor segmentation findings supplied by various specialists varied substantially (Sun et al., 2019). Semantic segmentation is a term used in computer vision to describe the categorization of an item at the pixel level. Automated segmentation of tumors in brain MRI is critical for prognostic, radiation strategy, chemotherapy planning, monitoring therapeutic efficacy, and surgical tumor removal planning (Chaddad et al., 2018).

Inside that field of artificial intelligence and computer vision, classification of images and segmentation is an important and broad subject. The process of adding captions to an image and classifying it into one of many predetermined classifications is known as image categorization. It is the most important and critical role, particularly in medical healthcare areas such as detecting, biomedical imaging, and properly identifying disease, which aids radiologists in improving investigative effectiveness and providing an improved path for surgical treatment (Srinivas et al., 2022). The separation of a digital image into several object segments often referred to as image objects or image regions, is known as image analysis in the context of digital image processing (sets of pixels). By reducing complexity and/or altering representation, segmentation aims to improve the comprehension and evaluation of a visual.

For classification and Localization of tumor, this paper proposes two primary techniques. Inception-V3 as base layer to achieved classification in the first method, with the addition of one extra layer of activation, normalization, and dense. The strength of repeated blocks was paired with a variety of convolution kernels in a multi-branch network topology. It is also distinguished clearly between the head (prediction), body (data processing), and stem (data intake). Since then, deep networks have continued to use this design pattern, where the stem is determined by the first two or three convolutions that process the object. They take the underlying object and extract low-level information from them. A body of convolutional blocks follows this. The head then associates the characteristics discovered thus far with the pertinent classification, Localization, detection, or tracking issue. The RESUNET model is used in the second strategy to segment and localize brain tumors using TCGA MRI data.

Key contribution (Figure 2) of this paper is as follow:

- To carry out the categorization procedure, utilize a generator of data that scales for the data from 0 to 1 and performs 0.1 validation.
- Putting forth a Deep Learning-based framework for automatically identifying and categorizing whether or not brain tumors are present.
- Compare the effectiveness of the suggested classification model to other deep learning models that have already been published.
- Create and train a localization model using REEUNET to pinpoint the tumor's location.

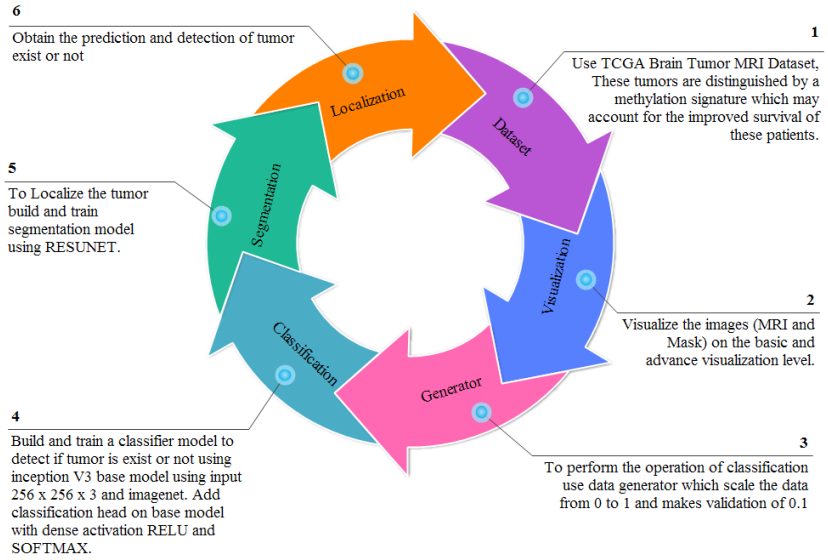

Figure 2. Step by step key contribution of this study.

The remaining portion of this article is structured as follows. Previous research was reviewed in Section 2, and the dataset and suggested technique are presented in Section 3. Section 4 is dominated for the model performance parameters. We reviewed the experimental findings in Section 5. Section 6 is discussion about the finding and dominated for comparison among existing models. Section 7 concludes this work with some concluding thoughts and future improvements.

2. Literature Survey

To make maximum advantage of the unsupervised learning (Ge and Santosh, 2021), authors suggest using deep semi-supervised learning. CNN with deep learning characteristics were merged into a novel semi-supervised learning with graph-based context for acquiring the labels of data samples, which includes a new 3D-2D continuous constraint for making consistent categorization for 2D slices from the very same 3D brain scan. Then, using both unsupervised and supervised methods with estimated labels, a deep-learning classifier is built to categorize various glioma kinds. To alleviate regularisation caused by medium datasets, CNNs are trained using synthetic MRIs created using Generative Adversarial Networks (GANs).

The neutrosophic set – expert maximum fuzzy-sure entropy (NS-EMFSE) technique was used to fragment image data in the first step (Özyurt et al., 2019). In the classification step, Features were mined from segmented brain images using CNN, which were subsequently classified using SVM and KNN classifiers. An investigational assessment was conducted utilizing cross-validation with 5-fold on 80 benign lesions and 80 hematological malignancies. When CNN features were combined with several classifiers, the findings indicated that they performed extremely well. The results of the simulations showed that CNN features had a greater performance of the classifier using SVM, with an average rate of success of 95.62 percent.

The recommended approach for medical image segmentation on an MRI image is based on contrast enhancement (SISR) and maximum fuzzy entropy segmentation (MFES) (Sert et al., 2019). Following that, pre-trained ResNet framework, which is an approach of convolutional neural network (CNN), and targeted classifier SVM are used to extract features and classify them (SVM). SISR was found to have an improved results in terms of brain tumor segmentation in experiments conducted. It also performed better when it came to identifying brain tumor locations, as well as malignancy brain tumors. As a result, the current study found that SISR has a 95 percent accuracy rate in the identification of segmented brain tumors, which is 7.5 percent higher than medical image segmentation using MFES without SISR.

In this paper, the authors (Ghosh and Santosh, 2021) provide a segmentation-based method for identifying brain cancers in MRI. They compare these two U-Net architectures (one with a baseline and the other with a ResNeXt50 framework) and a Feature Pyramid Network (FPN) that were validate and trained using the TCGA-LGG sample of 3, 929 images. The finest Dice coefficient is 0.932 for the U-Net design with ResNeXt50 cornerstone, whereas base U-Net and FPN have Dice values of 0.846 and 0.899, respectively. U-performance Nets using the ResNeXt50 backbone outperformed previous attempts.

The purpose of this research (Esmaeili et al., 2021) is to examine how effective specific deep-learning approaches are at detecting tumor lesions and separating them from healthy regions in magnetic resonance imaging comparisons. Regardless of the fact that there is indeed a significant relationship between category and tumor localized accuracy ($p = 0.005$, $R = 0.46$), the recognized AI arrangements examined in this learning detect specific tumor brains based on irrelevant criteria. The findings suggest that explainable AI strategies can help individuals progress a perception about model generalization and can be used to assess the success of deep learning systems. Comprehensible AI techniques will be an important part of improving interpersonal interaction and aiding in the selection of the optimal learning models.

The following research limitations are noted from the foregoing succinct evaluation of the closely related studies:

(i) Early studies that were published did not account for the class imbalance of training data between two classes, which led to one class having significantly worse performance, which therefore had an impact on the overall test performance.
(ii) In the study we found that most deep learning approaches and construction in brain tumor examination still contract with reinforcement classification, where the anatomical site of the patch leftovers unidentified for the network.
(iii) The most of the research is depend on the supervised learning technique, hence performance changes depending on the training dataset.
(iv) Need different network architecture and training strategies to optimize the feature selection methods as well as survival prediction in term of short-survivors, mid-survivors and long-survivors.
(v) In the next section of study, tried to overcome to above mentioned limitation.

3. Methodology Adapted

Machine learning (ML) and artificial intelligence (AI) are subsets of deep learning (DL) that deals with techniques that are inspired by the development of the brain and replicate how people analyze, gather, and interpret information. It is a crucial data science component that speeds up and simplifies data processing and pattern creation for decision-making (Kumar and Garg, 2018; Srinivas et al., 2022). It has learning networks that can learn either with or without human involvement (learn from labelled and unlabeled data). deep learning techniques reduce the amount of feature extraction required by supervised learning algorithms by compressing data, transforming images into main component-like structures, and creating network structures that minimize representational duplication (Muniasamy and Alasiry, 2020). The convolution neural network is the most well-known supervised machine learning architecture (CNN). This sort of neural network is taught using large amounts of data and has the capacity to extract feature representations using convolutions rather than manual extraction. There are three types of layers in this system: input, output, and hidden layers. Among the hidden layers are convolutional layers, ReLU tiers, max pooling, and connected layers. Convolutional neural systems are one of the most widely used techniques for deep learning for voice, word, and picture classification and identification (LeCun et al., 2015; Ker et al., 2017).

3.1 Dataset and Visualization

The Cancer Genome Atlas Glioblastoma Multiforme (TCGA-GBM) collection of data is part of a larger effort to build a scientific community committed to correlating cancer morphologies to genetics by supplying patient images linked to Cancer Genome Atlas people (TCGA). TCGA submitted a dataset with 3929 MRI scans with masks. The basic and advanced visualization of adapted dataset is visible in the Figure 4.

The next Figure 3 is showing the distribution of tumor and no tumor image classification.

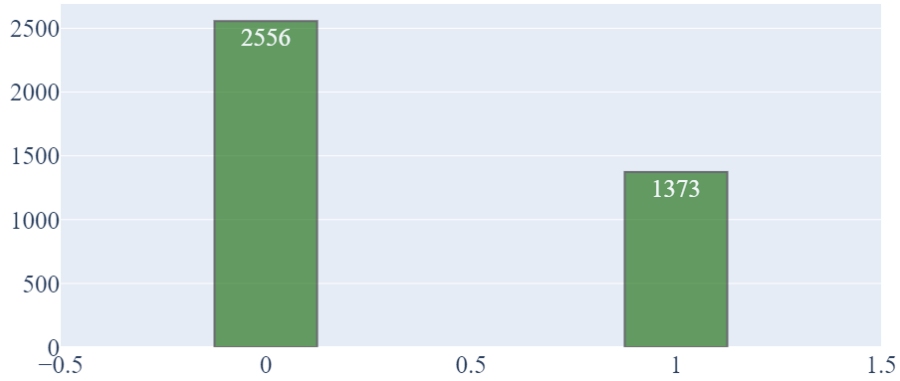

Figure 3. Distribution graph for tumor and no tumor.

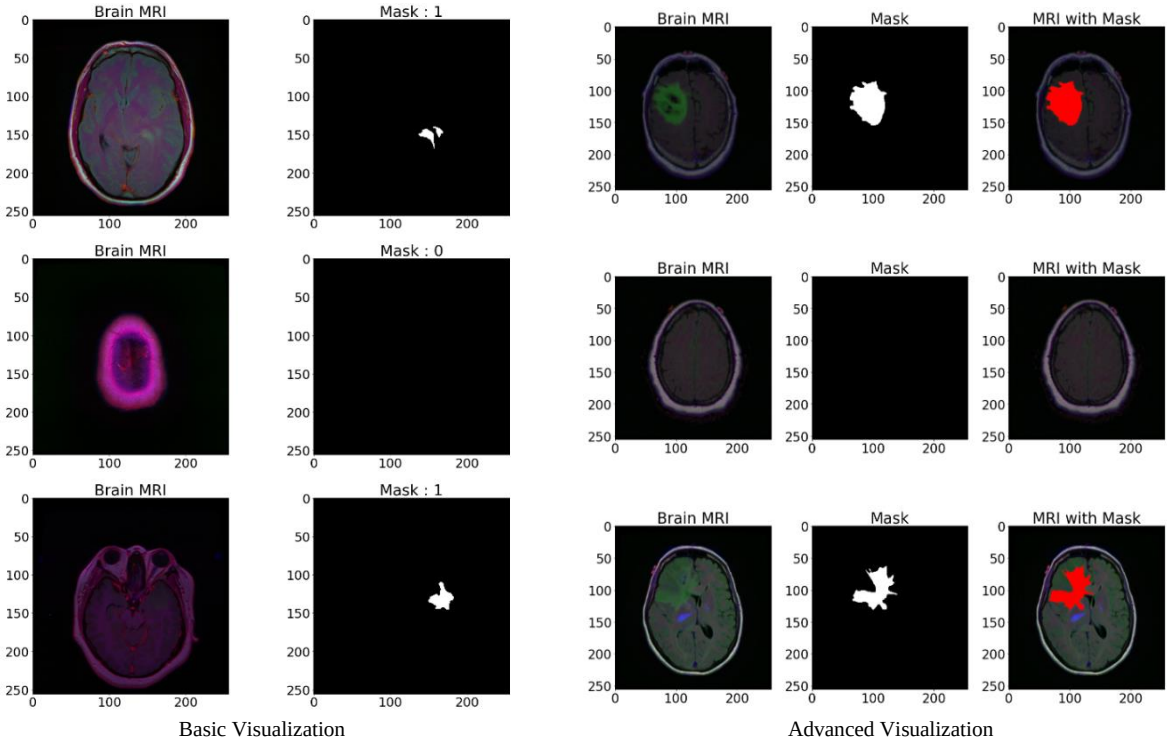

Figure 4. Visualization of TGCA MRI Scan.

3.2 Pre-Processing

The goal of the pre-processing stage is to increase picture quality, data cleansing, and MR image contrast. As per the adapted dataset firstly drop all the unnecessary data column from the set of data. After that convert the data in mask column to string format to use categorical mode. After that split the data into train, validation and test data (Table 1 and Figure 5). For the classification stage to create a data generator for train, test and validation with batch size 16, class mode categorical and target size 256 x 256. And to achieve the segmentation and localization, create a utilities file that contains the code for custom loss function and custom data generator.

Table 1. Split the dataset.

S No	Data	No of Images (Tumor and No-Tumor)
1	Train	2829
2	Test	786
3	Validate	314

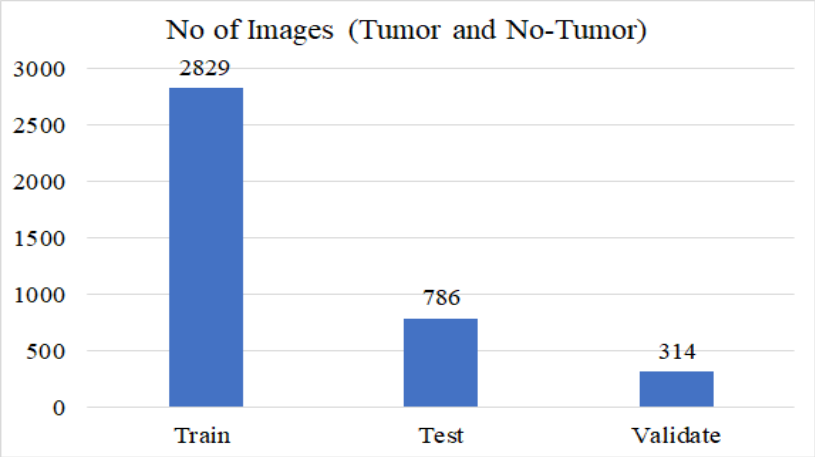

Figure 5. Split dataset.

3.3 Adapted Technique

3.3.1 Inception V3 Base Model for Classification

The third version of the inception frameworks, Inception V3 (Fettah et al., 2022), is distinguished by extra factorization principles. The Inception V3 image recognition model, which employs the batch standard to activate inputs and the Softmax to compute the Loss, includes convolutions, average pooling, max pooling, concatenations, dropouts, as well as fully - connected layers.

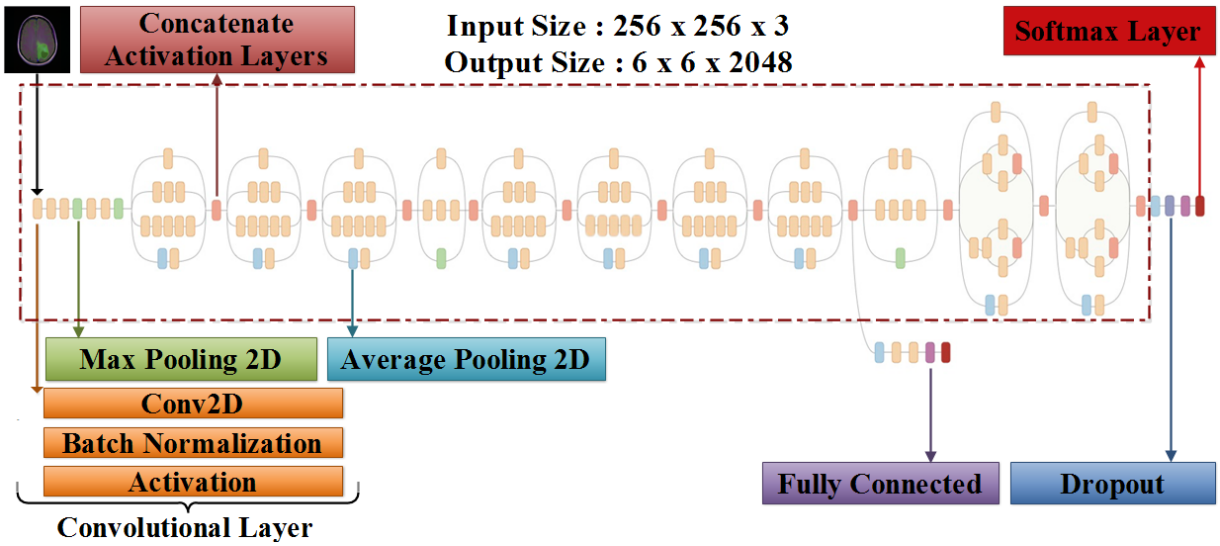

Figure 6. Inception V3 Model.

The inception V3 model (Figure 6) features 42 layers and a reduced error rate than previous models. The following are the primary changes made to the Inception V3 model:

(i) **Factorized Convolutions:** Reducing the number of factors in a network increases the complexity of the algorithm. It also keeps track of the network's efficiency.

(ii) **Smaller Convolutions:** Training proceeds more quickly when thinner convolutions take the place of larger ones. In contrast to a 5x5 convolution, which has 25 components, two 3x3 filters contain merely 18 (3x3 + 3x3) variables. (Figure 7).

(iii) **Spatial Factorization into Asymmetric Convolutions:** A 1x3 convolution accompanied by a 3x1 convolution might be used instead of a 3x3 convolution. The computational complexity would be significantly greater than the asymmetric convolution described if a 3x3 convolution was substituted with a 2x2 convolution (Figure 8).

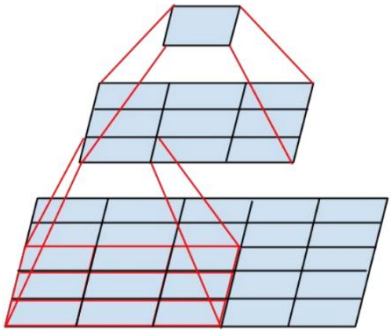

Figure 7. Smaller convolution.

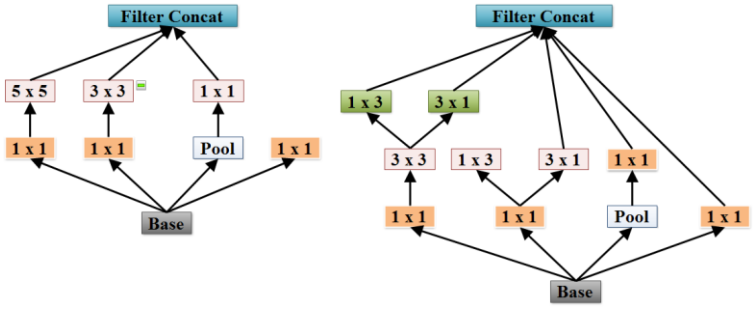

Figure 8. Spatial factorization into asymmetric convolution.

(i) **Utility of Auxiliary Classifiers:** To provide an auxiliary categorization between learning phases, a tiny CNN is used, and any losses it suffers are added to the overall network loss. Although they serve as a framework to guide in Inception V3, auxiliary categories were used for a deeper architecture in GoogleNet (Figure 9).

(ii) **Efficient Grid Size Reduction:** Pooling techniques are commonly used to reduce grid size. Furthermore, a more effective strategy is given to overcome computational complexity inefficiencies (Figure 10).

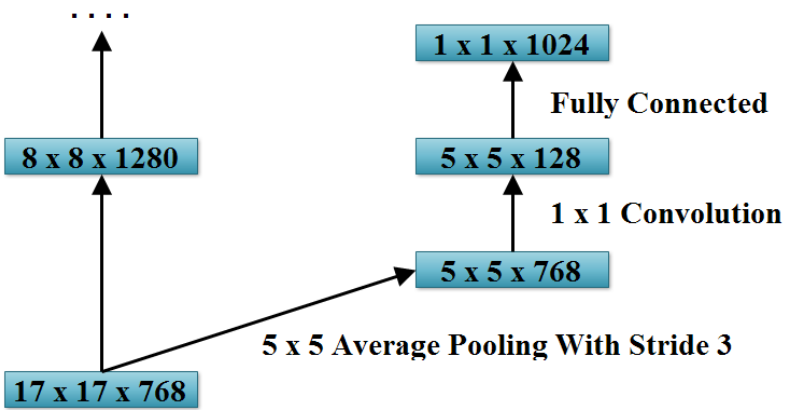

Figure 9. Auxiliary classifier.

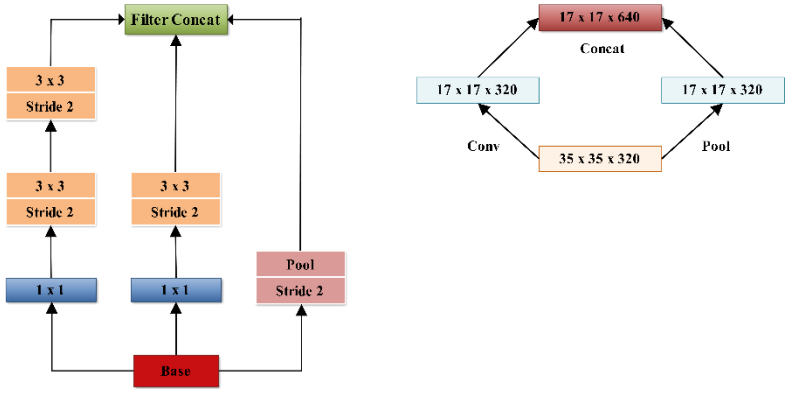

Figure 10. Grid size reduction.

3.3.2 RESUNET for Segmentation

RESUNET is the acronym for Deep Residual UNET. A convolutional semantic segmentation architecture was developed by Zhang et al. (2018). It was initially used to extract roads from high-resolution aerial photographs for the study of remote sensing data. With fewer parts and a fully convolutional neural architecture, RESUNET aims to deliver outstanding performance. Compared to the present UNET architecture, it is an improvement. Deep Residual Learning and the UNET architecture are both utilized by RESUNET (Figure 11).

The framework of research suggested brain tumor detection and localization technology is depicted in figure. To use categorical mode, first pre-process the TCGS MRI scan image by removing unnecessary columns from the dataset, converting the data in the mask column to string format, and splitting the dataset into train, test, and validate accordingly. Finally, create a data generator for train, test, and validate with batch size 16, mode of class is categorical and target size 256 x 256. To perform the operation of classification, add classification head with average pooling, flatten, dense layer for ReLU and SoftMax activation layer and dropout as well on the base model of Inception V3. This training model will perform using categorical cross entropy loss function and Adam optimizer. In the second phase to build and train a segmentation model for localize and detect the tumor with the help of the RESUNET architecture. In the pre-processing phase of this architecture, cut the data frame containing MRI's which has mask associated with them. Split the data into train and test then create utilities files that contain the code for custom loss functions and custom data generator. After that train segmentation model RESUNET implemented and at last predict and localize the tumor.

Following layer have been added in classification model:

- **Flatten Layer:** The process of flattening data into a one-dimensional collection for subsequent processing is known as flattening. In this study, the result of the convolutional layers is flattened to generate a single long feature representation. It's also interconnected to the final categorization model, known as a fully-connected layer.
- **Dense Layer:** Each neuron in the dense layer receives information from all other activation functions in the layer below, thus the name. It is a fundamental layer of neurons. Dense layers are used to detect characteristics based on the results of convolution layers.
- **Activation Layer:** An activation function for a neural network can be created and placed either at the beginning or in the middle. They influence whether or not the neuron fires. The input signal is modified in a nonlinear manner by the activation function. The following layer of neurons receives this changed output as an input.

- **Drop out Layer:** Dropout is a strategy for removing neurons from a neural network or ignoring them throughout development. In other terms, distinct neurons are recently suspended from the network.

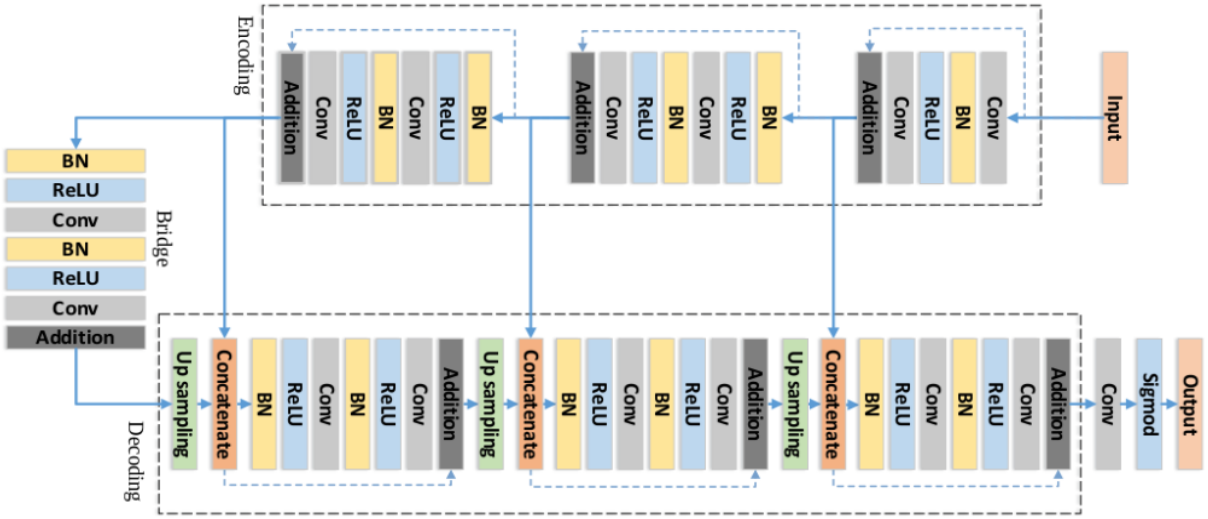

Figure 11. RESUNET Architecture Walkthrough.

Figure 12 presented methodology walkthrough of overall model.

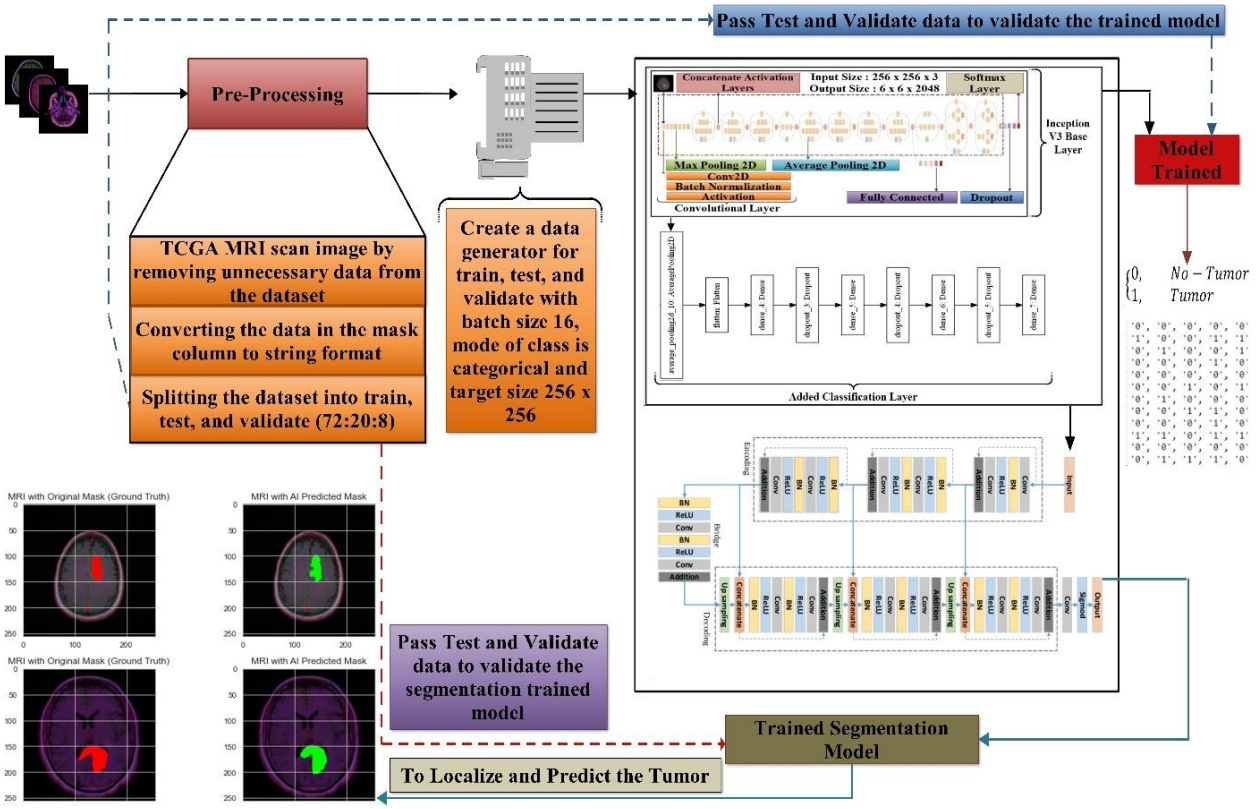

Figure 12. Adapted methodology walkthrough.

4. Model Performance Parameter

Accuracy: By using the input, or training, data, a model's accuracy is assessed by how effectively it can identify patterns and correlations between the variables in the dataset.

$$ACC = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

Precision: The accuracy is considered by dividing the amount of appropriately diagnosed Positive samples by that of the total number of Ture Positive data and False Positive Data (either correctly or incorrectly). The model's accuracy in classifying a sample as positive is evaluated.

$$Precision = \frac{TP}{TP+FP}. \quad (2)$$

F1 Score: A test's correctness is restrained using the F1-score or F1-measure. It is determined using the test's accuracy and recall.

$$F1\ Score = \frac{2\ TP}{2\ TP+FP+FN}. \quad (3)$$

Recall: Divide the total number of significant samples by the number of successful samples correctly categorized as positive to get the recall. The recall of the model influences how effectively it can discover Positive samples. The bigger the recall, the more positive samples found.

$$Recall = \frac{TP}{TP+FN}. \quad (4)$$

Tversky Loss: The Tversky index, which measures the overlap across two segmented objects, serves as the foundation for the Tversky loss. Presented is the Tversky index between such an object (Y) and the matching ground truth (T).

$$TI_c = \frac{\sum_{m=1}^{M} Y_{cm}T_{cm}}{\sum_{m=1}^{M} Y_{cm}T_{cm} + \alpha \sum_{m=1}^{M} Y_{cm}T_{c\prime m} + \beta \sum_{m=1}^{M} Y_{c\prime m}T_{cm}}. \quad (5)$$

where, c stands for the class, while c' stands for not belonging to class c. The number M represents the number of items in the first two Y dimensions. The weighting variables and regulate the amount that false positives and false negatives for each class contribute to the loss.

5. Results and Evaluation

Table 2 shown the accuracy of the classification model.

Table 2. Performance matrices for classification model.

S. No.	Performance Matrices	Results
1.	Accuracy	0.9996
2.	Loss	0.0025

Figure 13, Figure 14 and Figure 15 are shown the model performance of the classification in terms of the accuracy, loss and confusion matrix shown the predication for tumor (0 or 1). Classification report (Table 3) is another most important scenario that explain the overall observation for the model as suggested.

Table 4, Figure 16 and Figure 17 represents the performance of the localization of tumor. The Tversky Loss (TI) is a generalization of the Jaccard index and the dice coefficient as an asymmetric similarity metric.

Table 3. Classification report.

S. No.	Parameter	Precision	Recall	F1 Score
1.	0	0.96	1.00	0.98
2.	1	0.99	0.94	0.96
3.	Accuracy	0.97	0.97	0.97
4.	Micro Avg	0.98	0.98	0.97
5.	Weighted Avg	0.98	0.97	0.97

Table 4. Performance metrics for model.

S. No.	Performance Matrices	Results
1.	Tversky	0.9688
2.	Loss	0.0742

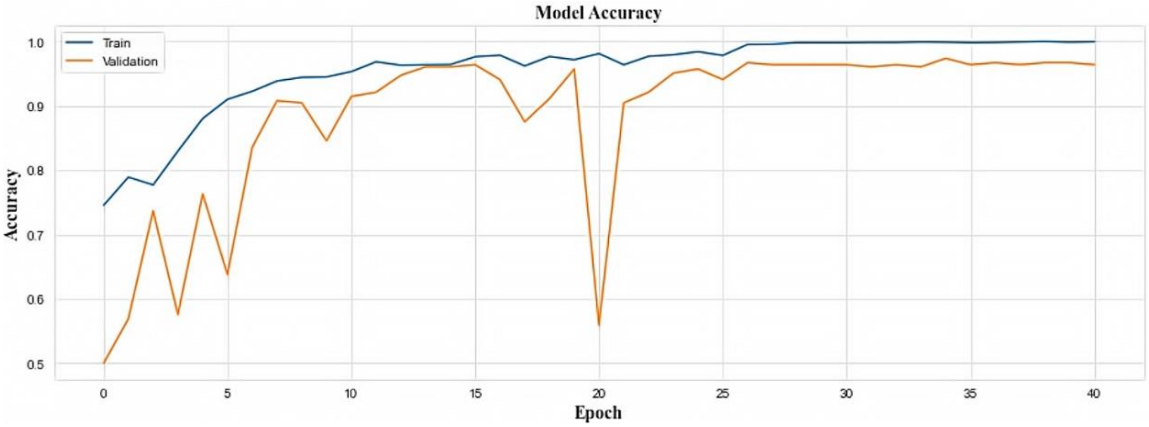

Figure 13. Performance graph for accuracy.

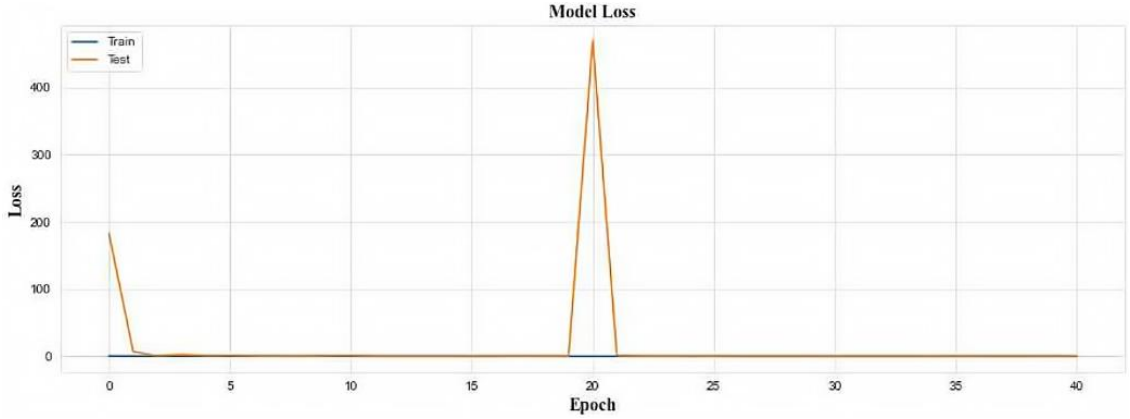

Figure 14. Performance graph for loss.

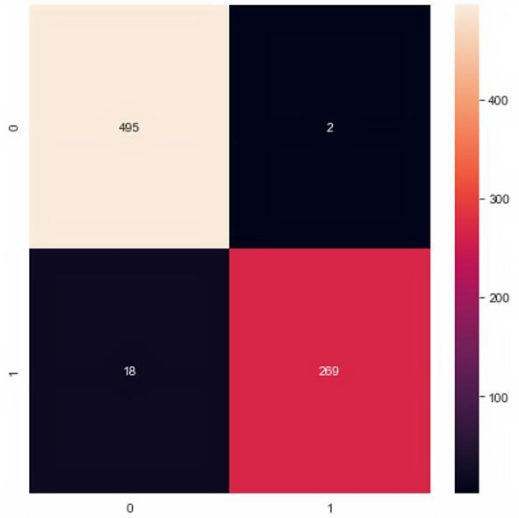

Figure 15. Confusion Matrix for classification model.

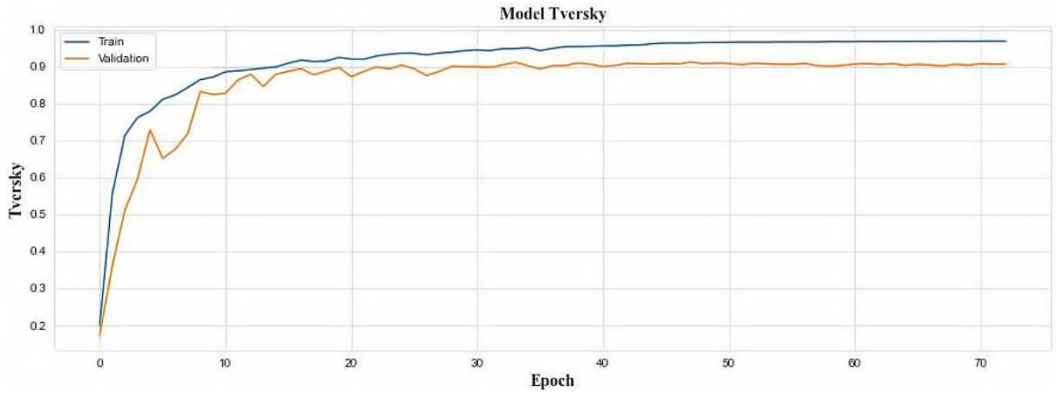

Figure 16. Model performance for Tversky.

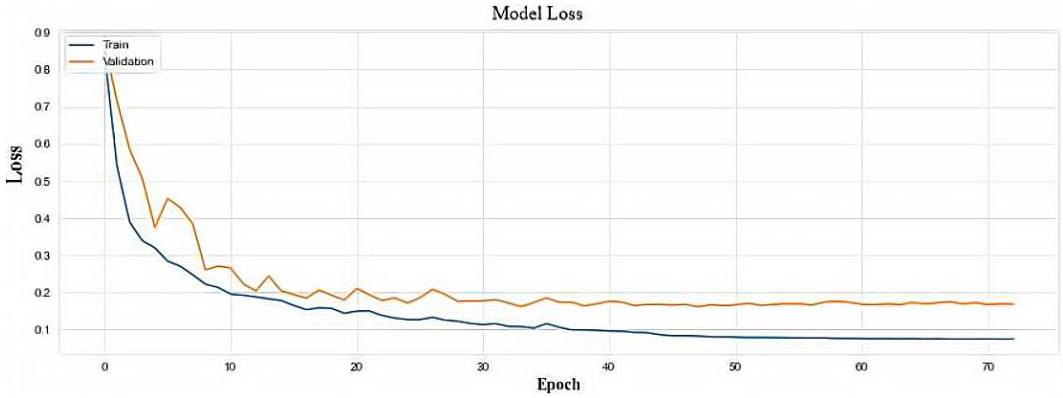

Figure 17. Model performance for loss.

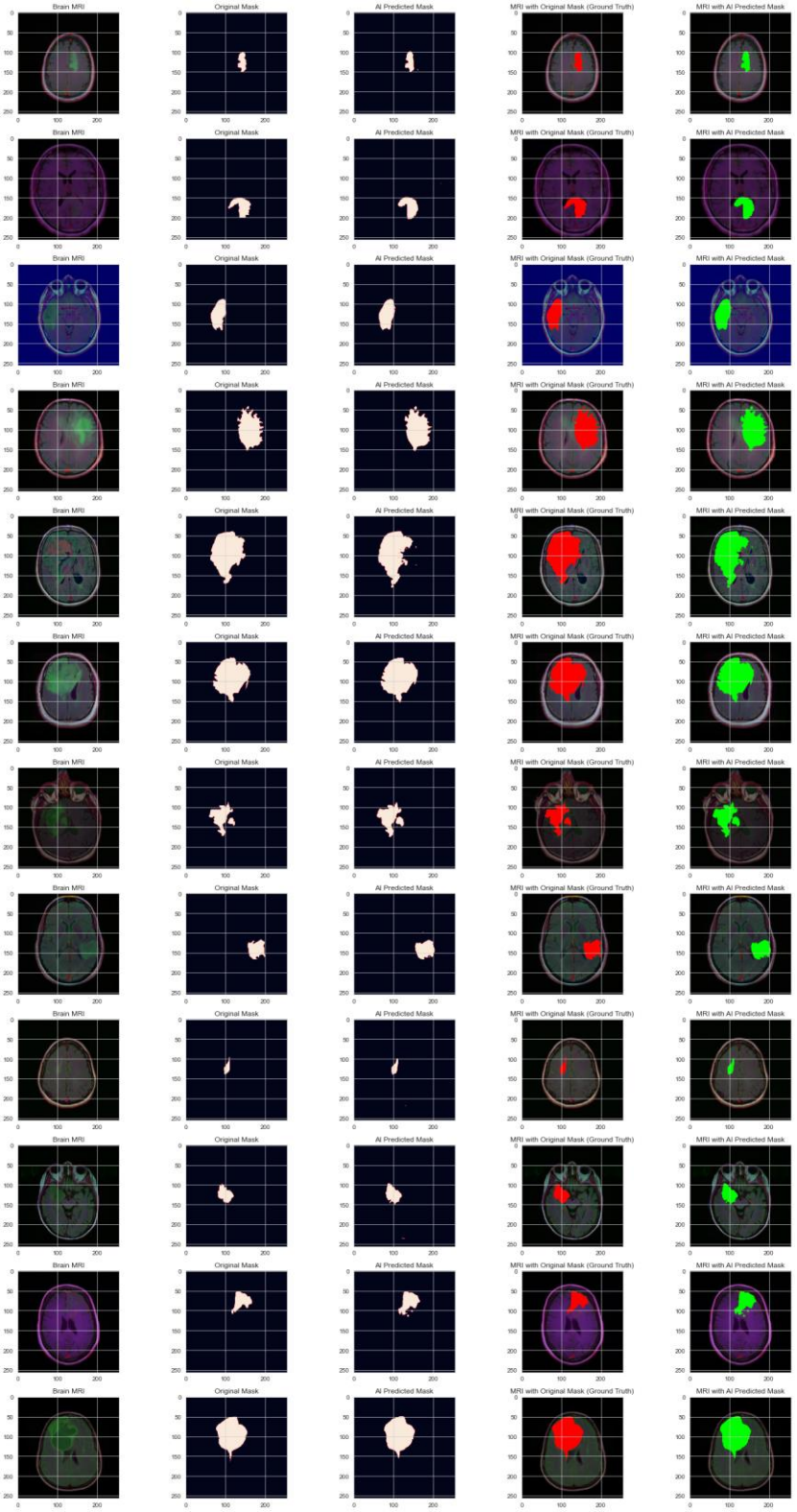

Figure 18. Localization of tumor and model prediction.

6. Discussion

Figure 18 shows that the localization of tumor and model prediction in terms of the tumor yes or no. The suggested model's performance is then compared to that of other approaches in the literature, with the findings shown in Table 5. These findings show that tailored Inception V3 used as Base Layer with RESUNET provides better results and clinical level pictures when compared to conventional approaches.

Some insights into the suggested approach may be drawn from our experimental findings:

(i) On the given dataset, high overall performance was attained in terms of whether the tumor was present or not.
(ii) Estimating the localization and predicting the presence or absence of a tumor is successful when Inception V3 is used as the base layer using the RESUNET technique.
(iii) The classification performance on the testing set has increased as a result of the addition of augmentation data to the training dataset for pretraining.
(iv) Large training data imbalances between classes are undesirable since they may produce noticeable performance variations between individual classes.
(v) The suggested strategy has achieved equivalent performance to fully supervised approaches, according to a comparison of results with multiple state-of-the-art methods.

Table 5. Comparison with existing methodologies (classification with localization).

S. No.	Reference	Model Adapted	Accuracy
1.	Ge et al. (2020)	CNN-GAN	0.8653
2.	Özyurt et al. (2019)	CNN-SVM	0.9310
3.	Özyurt et al. (2019)	CNN-KNN	0.8750
4.	Sert et al. (2019)	SISR-MFES-CNN	0.9500
5.	Ghosh and Santosh (2021)	UNET with RESNeXt50	0.9320
6.	Esmaeili et al. (2021)	Densenet-121	0.9210
7.	Esmaeili et al. (2021)	GoogLeNet	0.8730
8.	Esmaeili et al. (2021)	MobileNet	0.8890
9.	**Praposed Model**	**Inception V3 used as Base Layer with RESUNET**	**0.9700**

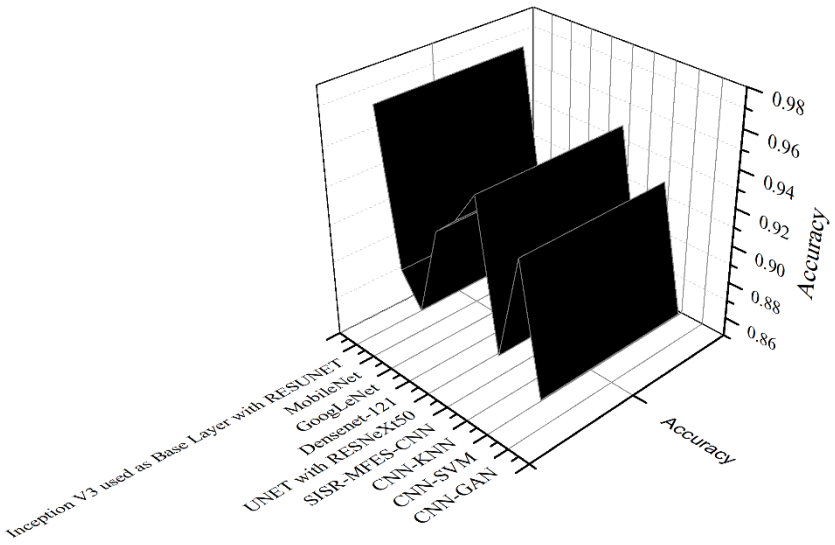

Figure 19. Comparison with existing methodologies (Classification with Localization).

7. Conclusions and Future Scope

In conclusion, study introduced a brain tumor categorization and segmentation methodological approach to determine the localization and prognostication of brain tumors to use the Inception V3 as a sublayer and a classification layer made up of machine learning techniques and from before the convolutional neural networks, this study uses a large number of pre-trained convolutional neural networks. Using the TCGA dataset, research conducted an exhaustive assessment in research investigation. The results of study experiments show that (i) Inception V3 is a great option if the MRI dataset is huge, and (ii) If the MRI dataset is huge, and the number of participants is high, RESUNET deep features is an excellent option (normal, tumor). In conclusion, suggested unique component ensemble approach helps overcome the limits of a single CNN model, resulting in improved and consistent performance, especially for big datasets. These findings suggest that suggested strategy for classifying brain tumors using an Inception V3 is appropriate. Although the performance of suggested method appears promising, more study is needed to minimise the model's size so that it might be employed in a knowledge distillation-based real-time medical diagnostic system. The accuracy of future work may be improved by integrating several classifiers with more effective localisation, feature extraction methods, and classification using real- and clinical-based instances by utilising big datasets encompassing many scenarios.

Conflicts of Interest

The paper has not been published before, and it is not currently being considered anywhere. There aren't any similar published manuscripts that I or my co-authors have authored either. There are no conflicts of interest, according to the author(s).

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