Chapter 6

Book Chapter

Recognition of Brain Tumors Using Deep Neural Networks Models

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Abstract

The identification of brain tumors is a significant issue in healthcare. A brain tumor is an abnormal tissue mass where cells multiply rapidly and uncontrollably. Image segmentation helps identify the tumor regions in the brain using MRI scans. Early detection of brain tumors is essential, which can be achieved with machine learning and deep learning algorithms. Our research used different deep learning methods, including VGG-16, ResNet-152, Inception-V3, Inception ResNet-V2, and a Custom Convolution neural networks model to categorize brain tumors. The sample dataset for our research consisted of 1085 tumorous

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and 980 non-tumorous images from the Kaggle online database. Among all the models, VGG-16 performed the best and achieved 98% accurateness in classifying brain tumors.

Keywords: Brain Tumor. Deep Learning. CNN. VGG-16. ResNet-152. InceptionV2.

1 Introduction

Brain tumors are the complex and life-threatening condition affecting millions worldwide. Early brain tumor detection is vital for efficient treatment and improving patient results.These tumors form because of aberrant cell development in the brain and can be benign or malignant (Al-Azzawi & Sabir, 2015; Havaei et al., 2017; Jia & Chen, 2024). Brain tumor symptoms vary according to the tumor's kind, length, and place, but frequent symptoms contain headaches, seizures, visual and hearing loss, and cognitive impairment. Brain tumor diagnosis is key for successful treatment and improved patient results. Traditional diagnostic procedures, such as MRI and CT scans, have drawbacks, such as high costs, long wait periods, and the requirement for professional interpretation (Mohsen et al., 2018; Pereira et al., 2016; Rammurthy & Mahesh, 2022; Rulaningtyas & Ain, 2009). Moreover, these methods can produce ambiguous results, leading to misdiagnosis or delayed diagnosis.

We have currently number of approaches for detecting tumors. The traditional method involves manual inspection by a radiologist, which can be time-taking and prone to errors. To address this issue, automated methods by machine learning and deep learning algorithms were developed for detecting and classifying brain tumors. Those methods utilize feature extraction techniques to gather pertinent information from MRI images. Deep learning has recently grown famous because it can discover patterns and features from massive datasets. Deep learning algorithms automatically learn hierarchical representations of data, allowing them to perform tasks like picture recognition, audio recognition, and natural language processing with high accuracy (Chen et al., 2020; Wang et al., 2019). Deep learning has produced outstanding outcomes in different medical imaging applications, including image processing and classification. Medical pictures, such as MRI and CT scans, are complicated and can contain many variables, making manual analysis challenging. Convolutional neural networks (CNNs) are a type of advanced artificial intelligence architecture that has demonstrated outstanding performance in analyzing and categorizing images (Bhanothu, Kamalakannan, & Rajamanickam, 2020; Chato & Latifi, 2017; Madhupriya et al., 2019). CNNs consist of multiple layers of filters that conduct convolutions on the data, helping them to learn patterns and features within the information. After the convolutional layers, there are pooling layers, which decrease the length of the data and streamline the information. Finally, fully connected layers use the learned features to classify the data (Choudhury et al., 2020).

Editors: S. Pandikumar, Manish Kumar Thakur
DOI:10.48001/978-81-980647-5-2-6 | ISBN: 978-81-980647-5-2

Feature extraction techniques are essential to detecting brain tumors using MRI images. These techniques aim to extract suitable information from the pictures. That can differentiate between healthy brain tissue and abnormal tissue indicative of cancer. Texture analysis is a commonly used feature extraction technique that involves extracting features related to the image's texture, such as contrast, homogeneity, and entropy (Arbane et al., 2021; Deepak & Ameer, 2021). Texture analysis can be used to differentiate between dissimilar kinds of tissue in the brain, such as gray matter, white matter, and tumor tissue. For example, tumor tissue tends to have a higher level of heterogeneity, which can be detected using texture analysis. Shape analysis is another feature extraction technique used for brain tumor detection, which involves extracting features related to the tumor's shape, such as size, volume, and surface area (Abdelaziz Ismael, Mohammed, & Hefny, 2020; Mohmmad & Sanampudi, 2023). These features can provide information about the tumor's spot and level, aiding in treatment planning.The intensity-based analysis is a third feature extraction technique for brain tumor detection. This technique involves extracting features related to the intensity of the image, such as mean, variance, and skewness. Tumor tissue tends to have a higher level of intensity than healthy brain tissue, which can be detected using intensity-based analysis.

This research compares multiple deep learning-based techniques to recognize brain tumors. The Deep Learning approaches such as VGG16, ResNet-152, Inception V3, Inception ResNet V2, and Custom Convolution Neural Network Model are evaluated to find the tumors in our brain, and VGG16 performed good compared to other models on the selected dataset of MRI scanned images from Kaggle. The similarity among these methods gives us a structural design that is fast, exact and needs a lesser amount of specialized facts, building it a practical implement for aiding medical professionals in the early detection and identification of brain tumors. Remainder of this research fully describes the suggested technique, experimental findings, and future work discussions. . The remaining of this research organized into sections: Section 2 gives overview of interrelated work in brain tumor identification with deep learning. Section 3 about suggested methodology, including the sample set of data, the CNN standards, their construction, and the research procedure. Section 4 for the testing outcome and the accuracy of the a variety of considered models. Finally,the researcher concludes in Section 5, where directions for future work are furnished.

DOI:10.48001/978-81-980647-5-2-6 | ISBN: 978-81-980647-5-2

2 Related Work

Jia and Chen's (2024) introduced an inventive approach called Fully Automatic Heterogeneous Segmentation using Support Vector Machine (FAHS-SVM), which employed deep learning techniques for brain tumor segmentation. The researcher proposed automated algorithm incorporating structural, morphological, and relaxometry information to separate the cerebral venous system in MRI images accurately. The segmentation function achieves a advanced of consistency among the anatomy and surrounding brain tissue. This research utilizes the Extreme Learning Machine (ELM), which consists of one or more additional layers of hidden nodes, as a learning algorithm in a variety of applications, together with regression and classification. The numerical results showcase an impressive accuracy rate of approximately 98.51% in noticing strange and normal brain tissue, emphasizing the performance of the future system. Havaei et al.'s (2017) proposes a method for segmenting brain tumors from Magnetic Resonance Imaging (MRI) using Deep Neural Networks (DNNs). The The paper emphasizes the significance of precise brain tumor segmentation in recognizing and planning treatment and discusses the challenges associated with traditional segmentation methods.The authors presented their DNN-based method as a strong solution to these challenges, demonstrating its effectiveness through a association with other state-of-the-art methods. They have used the 2013 BRATS dataset for this model. They got result as 87% on test data.

Khan et al.'s (2022) introduced a new approach that utilizes hierarchical deep learning to categorize brain tumors are 3 types: glioma, meningioma, and pituitary tumors. This process involves employing convolutional neural networks (CNN) in image processing, which utilize image fragments to guide the sample data and organize them into specific tumor types. The future system, called Hierarchical Deep Learning-Based Brain Tumor (HDL2BT) classification, achieves an impressive accuracy as 92.13% and demonstrates a low miss rate of 7.87%. Siar and Teshnehlab's (2019) article discusses the use of a Convolutional Neural Network (CNN) for the detection of brain tumors through Magnetic Resonance Imaging (MRI) images. CNN was also evaluated using other classifiers, and the accuracy ranged from 94.24% to 97.34%. The study also used Sensitivity, Specificity, and Precisions standards to calculate the performance of the network. The proposed method reached accurate of 99.12% on test data, demonstrating its potential for increasing the precision of tumor finding and treatment planning. The study highlighted the importance of accurate diagnosis by physicians, and using the future method can help progress the precision of diagnosis and increase the effectiveness of treatment.

Sajid, Hussain, and Sarwar's (2019) presented a deep learning-based method for segmenting brain tumors, specifically gliomas, using different magnetic resonance imaging modalities (MRI). The proposed method utilizes a hybrid CNN structure used to designed to consider together local and contextual information to prevent errors in diagnosis. The

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program also includes several steps to prepare the images for analysis and to remove any false positives. The method was experienced on a BRATS 2013 dataset and secured 86% accuracy. Woźniak, Siłka, and Wieczorek's (2023) introduced an approach called correlation learning (CLM) that significantly enhances the performance of deep neural network architectures by integrating them with classic architectures. By incorporating a neural support network, the CLM mechanism facilitated the identification of optimal filters for pooling and convolution layers within the CNN. Experimental model CLM model reached an outcome rate rounded of 96%.

Abdulbaqi et al.'s (2014) aim to proposed an enhanced approach for detecting brain tumors by utilizing a combination of Hidden Markov Random Fields (HMRF) and Threshold methods. A hybrid method is developed to accomplish this objective effectively. The paper presented a novel technique for tumor identification in MRI images, employing with above mentioned techniques. These approaches are useful to three distinct patient datasets and successfully differentiate homogeneous tissue regions within the brain tumor while preserving clear boundaries between different tissue constituents. Amin et al.'s (2019)introduced a method that used isolate the tumor area in Fluid Attenuated Inversion Recovery and T2 MRI scans using global thresholding and mathematical morphology operations. They combined LBP and GWT features to ensure accurate classification. The system's performance is evaluated using peak SNR, mean squared error (MSE). The T2 and Flair MRI scan results showed MSE values of 0.037 and 0.039 on the BRATS 2013 multimodal brain tumor segmentation challenge dataset. Amin et al.'s (2020) have tackled the issue by utilizing a deep-learning model to identify the tumors. A high-pass filter image is combined with the input slices to enhance the MR slices' quality and highlight any irregularities. The BRATS dataset was implemented in this research. By using the CNN model, this research reached a truth of up to 91% accuracy. Saba et al., 2020 have introduced fine-tuned a transfer learning model called VGG-19 to extract relevant features of brain tumor images. The above mentioned features merged manually crafted attributes such as shape and texture with optimized features using entropy. These combined features were then used to enhance accuracy and speed by inputting them into classifiers. To assess the model's effectiveness, it was assessed using well-known databases from BRATS datasets of 2015, 2016, and 2017. The outcomes showed impressively high dice similarity coefficients (DSC) of 0.97

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3 Proposed Methodology

In this model the tumors are used to identify based on the image processing with machine learning techniques. According to the model the dataset need to be collected related to the tumors of human's brain and applied the proper pre-processing techniques to perform the better classification. The steps involved in it are Image data acquisition, where the dataset is collected from reliable sources, the data, in this case, are images of brain MRI scans. Next, these collected images are pre-processed, where noise and normalization of the images are made. Next step, these pre-processed images are fed as input to the determined model, where the model training happens along with feature extraction. After the model training, the classification of these images occurs. lastly, the outcome of the considered models are evaluated according to the classification metrics. This model which will give the finest classification metric outcome is considered the accurate model. This model can be further used for deployment in real-time.

3.1 Dataset

The dataset used for training the models includes two classes: tumorous and non-tumorous brain MRI images.This dataset is taken from the online database Kaggle which is home to multiple datasets across many domains. In figure 1, the compiled image dataset contains two distinct classes of MRI scan images: tumorous and non-tumorous. These two classes form the compiled dataset used for training the models. We can effectively identify the variation between the tumorous and non-tumorous classes by visually inspecting these images. The link for the dataset is provided below.

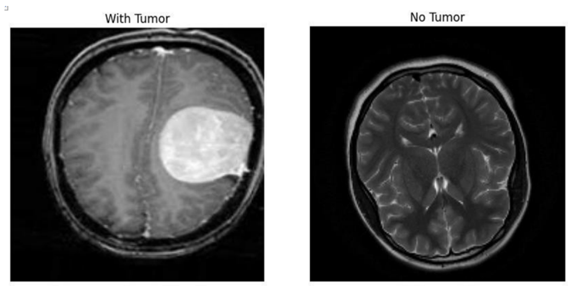

Figure 1. Sample images of dataset

We found 1085 images in the positive class (Tumorous) and 980 images in the negative class (Non-Tumorous). The bar graph in figure 2 illustrates this.

Let us consider some parameters to derive the categorization of Brain tumor images

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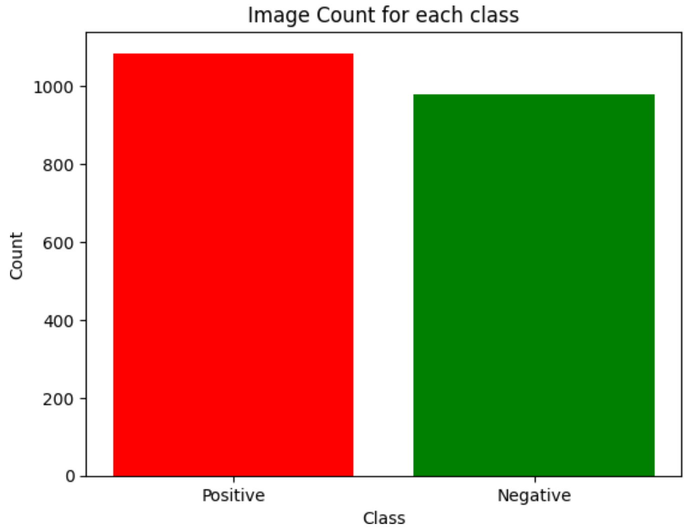

Figure 2. Image Count Visualization

through the chosen models for classifying these images.To begin with, let's consider the raw image dataset of brain tumor images as O, which consists of two classes determined as:

$$O = \{O_1, O_2\}$$

where O is the acquired dataset. O_1 is the positively labeled class of O, and O_2 is the negatively labeled class of O.

Let us consider the training dataset as O' and the validation dataset as O'', then:

$$O' = \{O'_1, O'_2\}$$

$$O'' = \{O''_1, O''_2\}$$

3.2 Data Pre-Processing

The samples of dataset are first read and resized to (160 x 160 x 3) to ensure uniform size. Any empty pixels formed during resizing are filled using an interpolation algorithm. Image normalization is adjusting an image's intensity values to make it more consistent and suitable for further analysis or processing. It It involves scaling the pixel values of an image into a standardized range, usually between 0 and 1 or -1 and 1.Normalization helps to remove inconsistencies in illumination, color, and contrast, which differences in

DOI:10.48001/978-81-980647-5-2-6 | ISBN: 978-81-980647-5-2

acquisition devices, lighting conditions, and image resolution can cause. The resized images from the previous step are normalized by dividing them by 255. The compiled dataset consists of 2065 images from both classes. To effectively train the model, it is necessary to divide the sample data into two sets: the training set and the validation set. The training set is used to prepare the models, while the validation set is used to authenticate the model during runtime and test it. Table 1 below represents the data split.

Table 1. Data Split Percentages

Data Type	Percentage
Training	80%
Validation	20%

The table 1 determines that the data is split 80-20 as the trained data and test data from the compiled dataset acquired from the Kaggle database, The figure 3 determines the number of images split into training and validation sets.

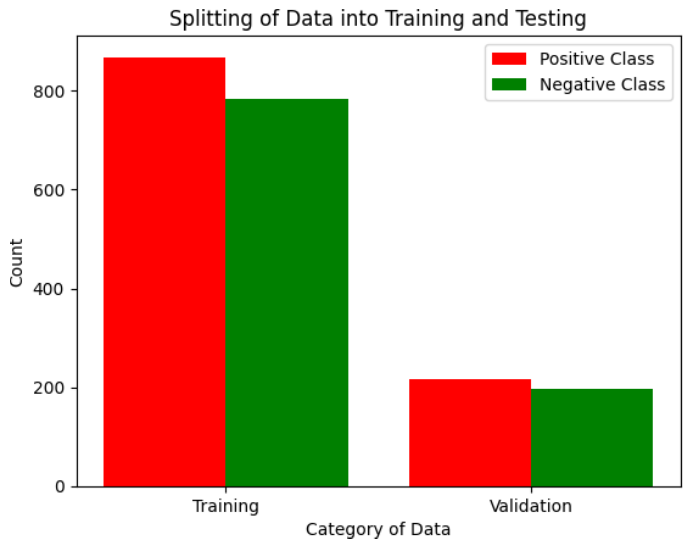

Figure 3. Data Split Visualization

DOI:10.48001/978-81-980647-5-2-6 | ISBN: 978-81-980647-5-2

3.3 Implementation

The primary models used to detect brain tumors rely on CNNs, which are commonly employed for image classification tasks. One of CNNs' main advantages is their capacity to automatically understand characteristics from input data instead of depending on manually crafted features, as seen in traditional computer vision algorithms. The models that detect brain tumors include VGG-16, ResNet-152, Inception-v3. Inception-ResNet-v2, and a custom CNN.

VGG-16 is a convolutional neural network with 16 layers, including 13 convolutional layers and 3 fully connected layers. The network has a straightforward design with 3x3 convolutional filters and max pooling layers. ResNet-152 is a CNN architecture that incorporates residual connections to tackle the issue of vanishing gradients and facilitate the training of deep networks. This network consists of 152 layers, and it uses skip connections to allow dispatch to flow directly from one layer to another. Figure 4 represents the VGG-16 and ResNet-152 Compiled Architectures. Inception-v3 is a CNN architecture that uses multiple parallel convolutional layers, which are combined using concatenation. The network has a "stem" layer that performs dimensionality reduction before branching out into multiple parallel convolutional layers, including Inception modules that use filters of different sizes to capture features at different scales. Inception-ResNet-v2 is a combination of the Inception-v3 and ResNet architectures. The network has residual connections between the Inception modules, allowing for better gradient flow and improved training of the network. It also features "multi-branch" layers that allow the network to capture characteristics at several scales, as well as "shortcut" connections that enable information to flow directly from one layer to another. Figure 5 illustrate the Inception-V3 and Inception ResNet-V2 Compiled Architectures.

A custom CNN is a convolutional neural network architecture uniquely designed for a particular task.

Customizing a convolutional neural network's architecture can allow researchers to tailor the model to the specific requirements of a particular task. This may include adjusting the number of layers, filters, pooling operations, and other hyperparameters to optimize the model's performance for the given problem.The objective is to create an optimized and best-suited model for the particular task. By modifying the architecture, researchers can fine-tune the model to enhance its accurateness and effectiveness for this given problem. The design of a custom CNN model typically involves several stages. The first stage is data preparation, where the input data is preprocessed and augmented to improve the model's generalization capabilities. The next stage is the design of the architecture, which involves deciding on the number of layers, filter sizes, activation functions, pooling methods, and other hyper parameters. The architecture defined for a custom CNN for this problem consists of an input layer, 6 convolutional layers, 3 max-pooling layers, and 3

DOI:10.48001/978-81-980647-5-2-6 | ISBN: 978-81-980647-5-2

dense layers, which are utilized to organize the Brain MRI Images into their respective classes.

Figure 6 shows the Custom CNN Compiled Architecture.

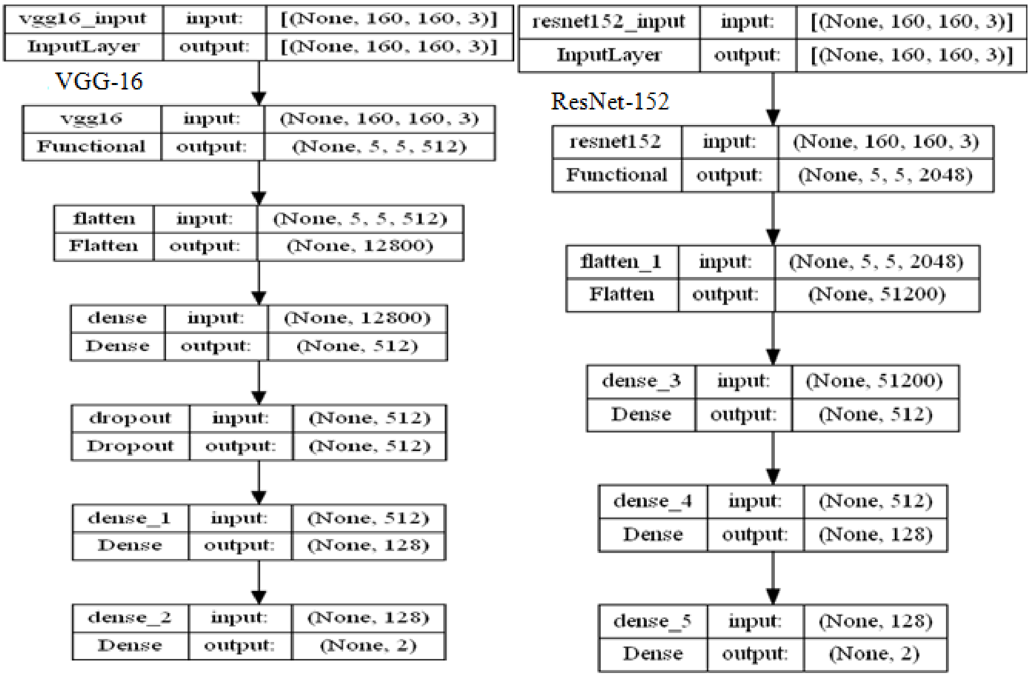

Figure 4. VGG-16 and ResNet-152 Compiled Architectures respectively

DOI:10.48001/978-81-980647-5-2-6 | ISBN: 978-81-980647-5-2

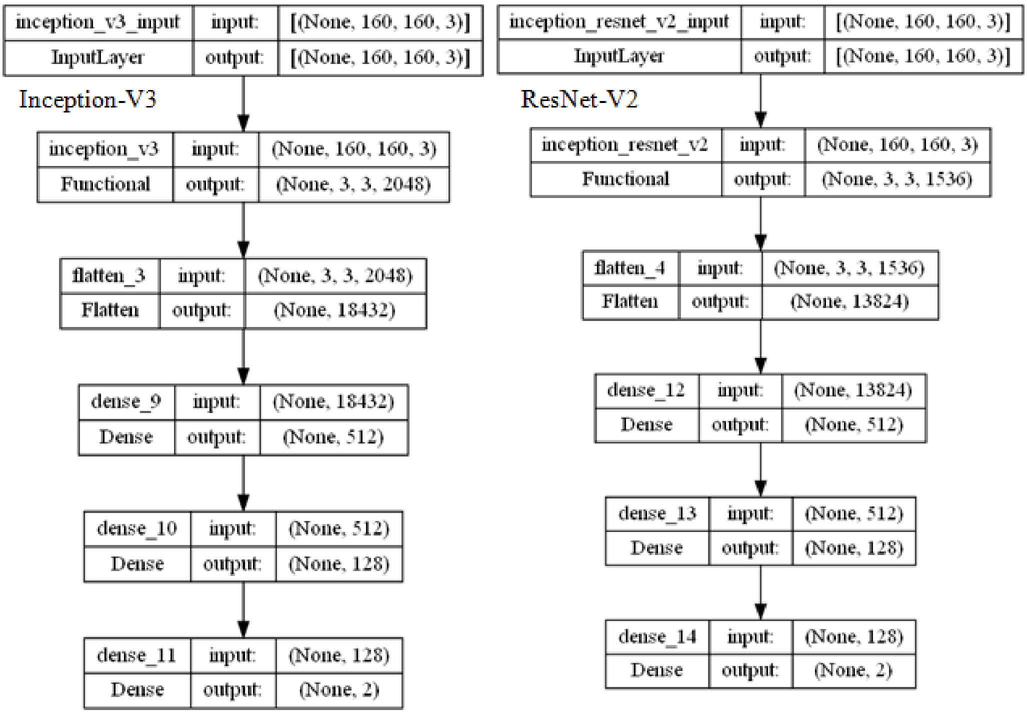

Figure 5. Inception-V3, Inception ResNet-V2 Compiled Architectures respectively

DOI:10.48001/978-81-980647-5-2-6 | ISBN: 978-81-980647-5-2

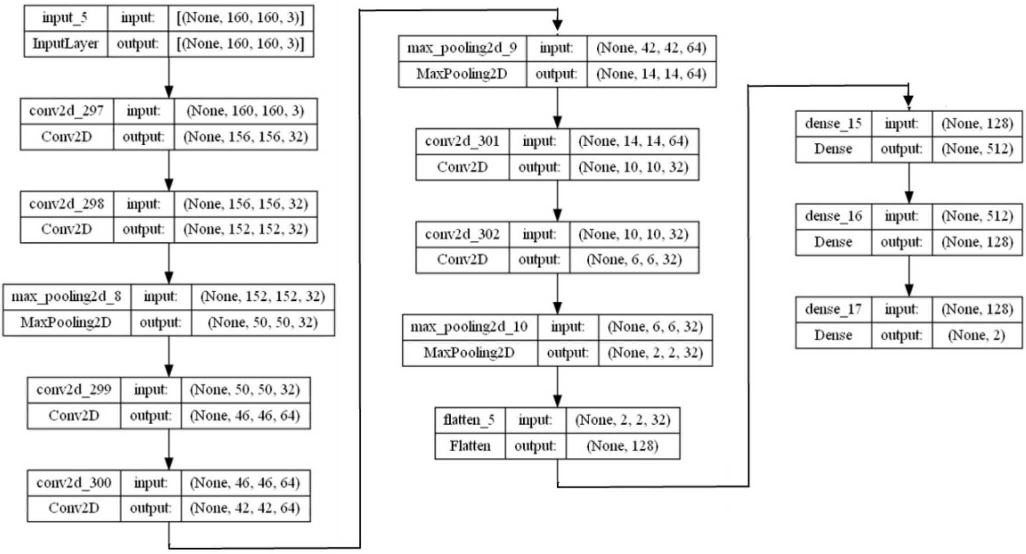

Figure 6. Custom CNN Architecture

4 Experimental Results

This part is about the results produced by the models that have been determined previously. The results obtained from all five models are presented below, and a comparison is made between them. The objective of this researcher is to realize how each model performed in relation to the others. This analysis provides an in detailed view of the comparison between the models executed above, below are the graphs for various results. Figure 7 interpret the Training precision and Loss graphs of all the five models. Figure 8 interpret the Validation Accuracy and Loss graphs of all the five models.

Table 2 shows how accurate and how much loss different models had. Figure 9 shows the ROC curve for all the models. VGG16 and Inception ResNet V2 models performed consistently well during training and validation. On the other hand, ResNet 152 and the Custom CNN model had more ups and downs in their performance. The graphs show these ups and downs in precision and loss over 20 iterations. Also, VGG-16 had the best accuracy and lowest loss in both training and validation compared to the other four models.

DOI:10.48001/978-81-980647-5-2-6 | ISBN: 978-81-980647-5-2

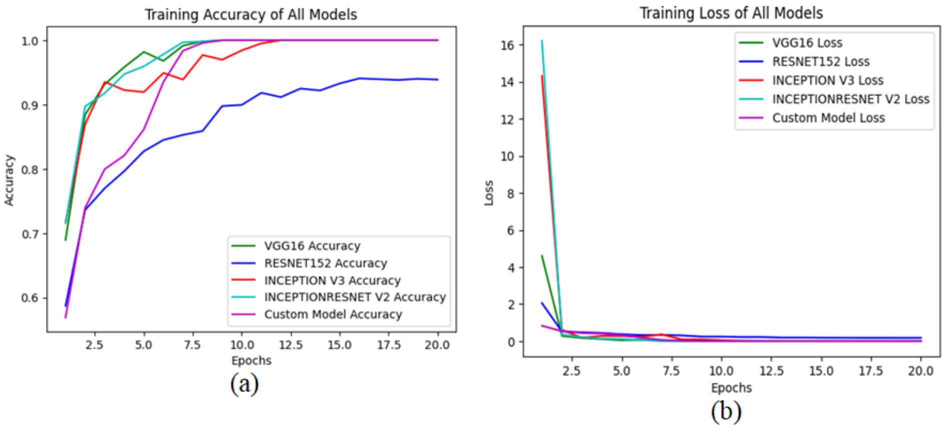

Figure 7. (a)Various models Training Accuracies (b) Various models Training loss

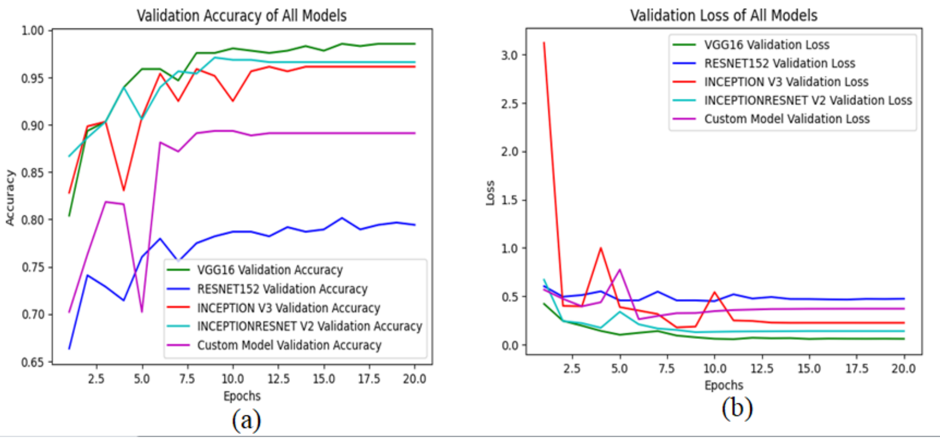

Figure 8. (a)Various models Validation Accuracy (b)Various models Validation Loss

Table 2. Accuracy and Loss Values

Model	Accuracy	Loss
VGG-16	97%	0.005
ResNet-152	89%	0.232
Inception V3	96%	0.065
Inception ResNet V2	96%	0.037
Custom Model	95%	0.052

DOI:10.48001/978-81-980647-5-2-6 | ISBN: 978-81-980647-5-2

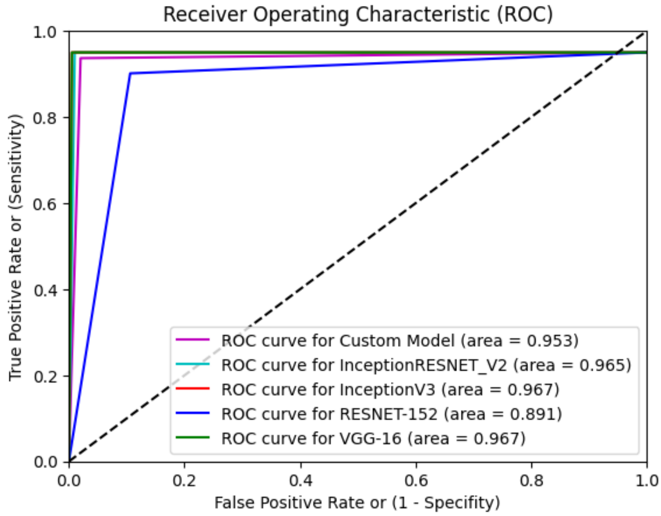

Figure 9. ROC Curve for all the models

5 Conclusion

Brain tumor discovery is an important area of medical study that has come a long way in recent years. We have implemented VGG-16, ResNet-152, Inception-V3, Inception ResNet-V2, and Custom CNN models to classify brain tumors by using an image classification dataset. According to our experiment, VGG-16 classification performed effectively compared to all other models and achieved 98% accuracy. The possibility of brain tumor recognition will make bigger further in the future, and new diagnostic and imaging technologies will continue to be developed. We guess to see additional breakthrough and enhancements in this field in the near future

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DOI:10.48001/978-81-980647-5-2-6 | ISBN: 978-81-980647-5-2