Brain Cancer Detection From MRI: A Deep Learning Approach

Abhilipsa Padhy[a] and Ishan Das[a]

[a]VIT AP UNIVERSITY, AMARAVATHI, Vijayawada, 522241, Andhra Pradesh, India

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ABSTRACT

Among all the diseases that harm humans, Cancer is one of the most harmful. One of the main procedure to detect cancer is through MRI. Tumors are excess cells that grow in an uncontrolled way and are one of the most common causes of cancer. Among the various types of tumors, brain tumors are more dangerous and needs immediate medical attention. MRI Imaging play an important role by helping doctors in diagnosis, analysis and treatment planning of brain tumor. MRI Images provide better results than CT scan, Ultrasound and XRay. Deep learning with image classifier can be used to efficiently detect cancer cells in the brain through image processing of the MRI images which results in saving invaluable time of surgeons and Radiologists. This paper focuses on the various image processing technique to automate brain cancer detection. In the proposed paper the deep learning architectures such as RNN, VGG19, Resnet50 and InceptionV3 are used to detect and recognize the brain tumor. Here in total 3900 MRI images were used out of which all most half were cancerous and the other half were normal to help test, train and validate the detection of brain tumor.

1. Introduction

Human body is made up of several type of cells. Among them Brain is a highly specialized and sensitive organ of the human body. A brain tumor is basically the growth of excess cells in the brains or near it. Brain tumor is one of the most harmful disease for a human being. Curing cancer has been one of the major diseases that researchers have been unable to solve, and research around cancer take a lot of money and man-hours' brain tumor can be either non-cancerous or cancerous and malignant . Science still hasn't been able to find all the root causes of cancer and innovate safer and more successful methods to shut them down .Brain tumors are easily curable in its early stage and very benign in nature but once the tumor is neglected and not cured in time , it starts to spread the tumor turns malignant and becomes cancerous . These cancerous cells can further invade and destroy brain tissues.

Brain tumor diagnosis is also another major issue and it is very difficult to accurately diagnose a brain tissue due to diverse size , shape, location and appearance . Around 250,000 people are affected by brain tumors every year, with 2 percentage of those cases being confirmed as malignancies. It is quite difficult to detect a brain tumor in it's early stage due to its small size and undefined shape . The best way to know the possibility of a tumor is through Magnetic resonance Imaging (MRI) . MRI normally provides with better and more accurate data than Computed Tomography (CT) because Magnetic resonance Imaging provides greater contrast between the soft tissues of human body , hence the MRI is the most effective method to detect brain tumor.

MRI (Magnetic Resonance Imaging) scans are is a type of imaging technique which uses magnetic fields and radio waves to deconstruct and reconstruct the internal structures of the body. It provides valuable information about soft tissues, such as the brain, spinal cord, organs, muscles, and joints. The MRI images that are used for detecting brain tumor first goes through image processing and image enhancement tools to improve the quality of the images . In this model contrast adjustment and threshold techniques are used to highlight the features of the MRI images.

In this paper after the feature extraction, we aim to explore the effectiveness of CNN based model in accurately detecting brain cancer from the dataset.

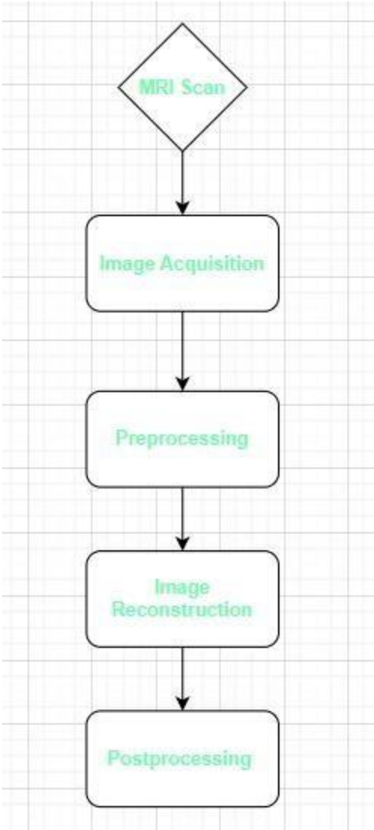


Figure 1: Block Diagram of Digital Image Processing to Extract Features

We will analyse the performance of various CNN architectures, including VGG19, Resnet50 . We will also investigate the impact of using Inceptionv3 and RNN to analyse the difference in the learning rate and performance of the model according to the batch size.

The findings of this research can contribute to the development of more accurate and efficient detection of brain tumor . Moreover it can also provide insights to the potential of deep learning techniques in advancing the field of tumor and cancer detection .

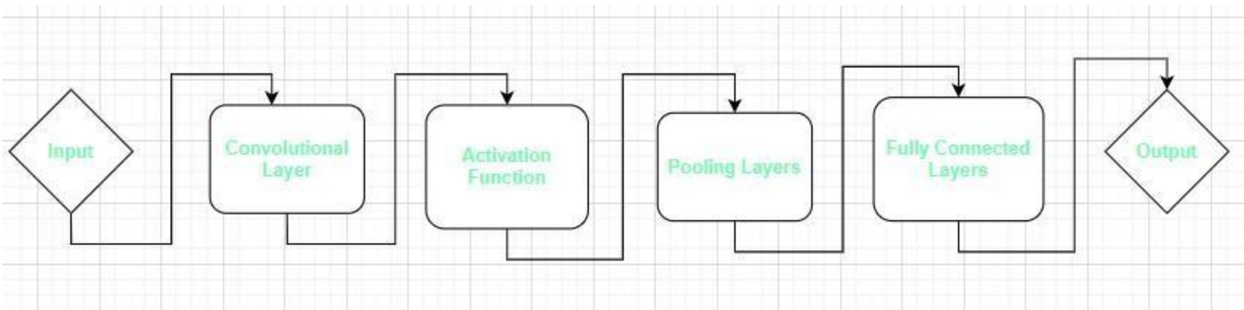


Figure 2: Overview of Structure of CNN

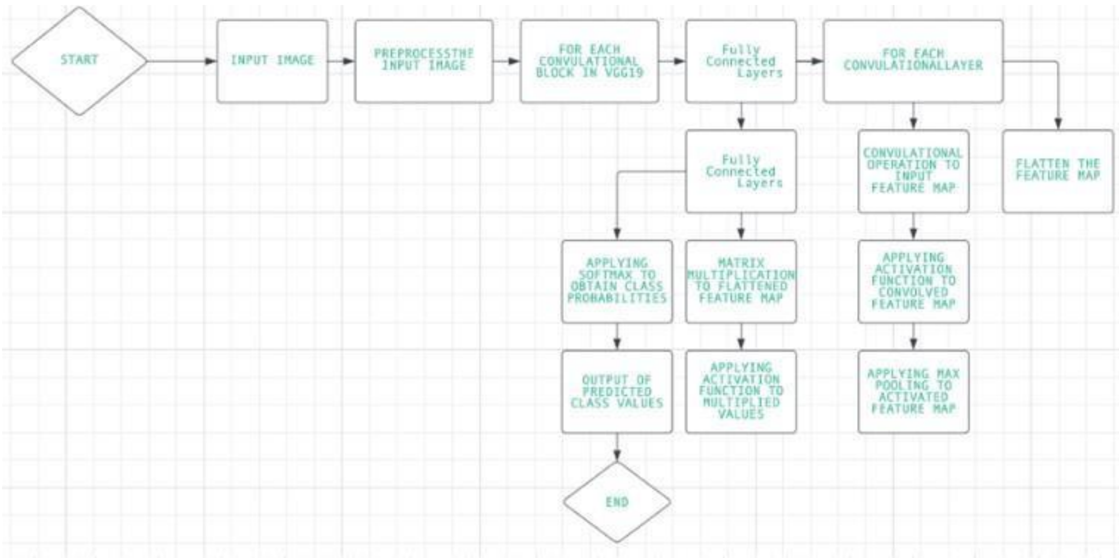


Figure 3: Overview Flowchart of VGG19

2. Related work

According to Havaei et al. (2017) in "Deep Learning for Brain Tumor Detection and Segmentation": This paper proposes a deep learning framework for autonomous brain tumor recognition and segmentation using 3D convolutional neural networks (CNN). The model obtained competitive performance on the BRATS (Multimodal Brain Tumor Segmentation) competition dataset. Now Pereira et al. published "Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images" in 2016: This research describes a CNN-based approach for segmenting brain tumors in MRI images. The proposed approach accomplishes exact tumor detection by training a deep network on a large dataset of annotated brain pictures.

"Brain Tumor Detection and Classification Using Histogram Analysis of MRI Images" was published by Patel and Mishra (2017): The study emphasizes the use of histogram-based features in distinguishing tumor from non-tumor regions.

"Brain Tumor Detection and Segmentation Using Texture Analysis and Hierarchical Classification" was published by Moradi et al. (2015): This work detects and segments brain tumors using texture analysis and hierarchical classification methods. The study investigates the capacity of textural features extracted from MRI images to discriminate between tumor and healthy tissue.Rathore et al. (2019) published

"Computer-Aided Diagnosis of Brain Tumor Using MRI Images: A Survey": This review research provides an overview of computer-aided diagnostic (CAD) systems for identifying brain tumors using MRI images. It looks at a variety of image processing techniques, machine learning approaches, and deep learning methods that are employed in the area.

"Automatic Brain Tumor Detection and Segmentation Using U-Net Based Fully Convolutional Networks" by Kamble and Tarte (2019): This research proposes a U-Net-based fully convolutional neural network for autonomous brain tumor identification and segmentation. The algorithm also produced accurate results and discoveries on a publicly available brain tumor dataset.Yasmin Mussarat, Amin Javeria, Sharif Muhammad, Raza Mudassar, and Amin Javeria Journal of Ambient Intelligence and Humanized Computing Online Publication, 2018. Prof. Gonge Sudhanshu, Nalbalwar Rajeshwar, Majhi Umakant, Patil Raj, and Nalbalwar Rajeshwar 2014 Brain Tumor Detection Using ANN International Journal of Research in Advent Technology 2.Dogantekin Esin, zyurt Fatih, Sert Eser, Avci Engin, and zyurt Fatih 2019 Elsevier Ltd 147 Brain tumor diagnosis based on Convolutional Neural Network with neutrosophic expert maximum fuzzy sure entropy.

"DeepRadiologyNet: Radiologist-Level Detection of Acute Intracranial Hemorrhage on Head CT Scans" by Chang et al. (2018): This paper proposes a deep learning model for identifying acute intracranial bleeding (a kind of brain tumor) on head CT scans. The model outperformed radiologists in terms of detecting and localizing hemorrhages. "Deep Learning-Based Automatic Detection of Malignant Pulmonary Nodules on Chest Radiographs" by Shen et al. (2019): This work focuses on the automated identification of malignant pulmonary nodules, which can indicate lung cancer, using deep learning models applied to chest radiographs. Deep learning has the potential to help in the early detection and diagnosis of lung cancer, according to the study.

Kamnitsas et al. (2017) published "DeepMedic for Brain Tumor Segmentation."DeepMedic, a deep learning architecture for automated brain tumor segmentation from MRI images, is introduced in this research. DeepMedic employs a multi-scale, multi-path 3D CNN to gather both local and global context information for precise tumor segmentation.

Chang et al. published "Deep Learning-Based Classification of Glioma Using Conventional MRI Images" (2018)The authors suggest utilizing conventional MRI scans to classify glioma brain cancers using deep learning. They use a deep CNN architecture to obtain excellent accuracy in differentiating different glioma grades, allowing for more tailored treatment planning.Kamnitsas et al., "Automatic Brain Tumor Detection and Segmentation Using U-NetBased Convolutional Neural Networks" (2017).This work introduces a U-Net-based architecture for automatic brain tumor detection and segmentation. The U-Net model effectively captures contextual information through a symmetric encoder-decoder structure, enabling precise segmentation of tumor regions.

"Glioma Grading using Deep Convolutional Neural Networks" by Ismail et al. (2018).The authors propose a deep CNN-based approach for glioma grading from MRI images. Their model accurately classifies glioma tumors into lowgrade and high-grade categories, providing important information for treatment planning and prognosis prediction.

3. Literature Survey

1.1. Comparitive Analysis

The comparative analysis of the mentioned approaches for brain tumor detection and

segmentation is provided below.

1. Deep Medic for Brain Tumor Segmentation:
   DeepMedicforBrainTumorSegmentation utilizesamulti-scale,multi-path3DCNNarchitectureandtheBraTS dataset, achieving superior brain tumor segmentation accuracy in the BraTS competition. Despite its success, the model’s high computational complexity may limit its real-time applicability.
2. Automatic Brain Tumor Detection and Segmentation Using U-Net-Based Convolutional Neural Networks: Automatic Brain Tumor Detection and Segmentation Using U-Net-Based Convolutional Neural Networks employs the U-Net architecture on the BraTS dataset, demonstrating cutting-edge performance in brain tumor segmentation. However, its memory-intensive design may pose challenges with computing resources, particularly for high-resolution volumetric data.
3. Deep Learning-Based Automatic Detection of Brain Tumor Using MRI Images:

1 .2. Dataset Description

The selection of important features from the dataset plays a crucial role in any Deep Learning model's success. In this proposed project the dataset was acquired from various online resources from Kaggle .The dataset contains a total of 3900 Images , out of which 3500 were used as train images which helped the model train to detect the brain cancer , 250 images for validation and remaining 150 for testing. The model contains a total of 65 convolutional layer ,16 being from VGG19 and 49 from Resnet50. It also contains 168000000 parameters and 169 000000 gradients and 336 GFLOPs.

DeepLearning-BasedAutomaticDetectionofBrainTumorUsingMRIImagesutilizesadeepCNNontheBraTS dataset, achieving excellent accuracy in detecting and segmenting brain tumors. Nonetheless, its performance may vary based on tumor characteristics and image acquisition protocols.

4. A Deep Learning-Based Framework for Brain Tumor Segmentation and Survival Prediction: A Deep Learning-Based Framework for Brain Tumor Segmentation and Survival Prediction combines 3D CNNs to accurately segment brain tumors and predict patient survival, showing promise for treatment planning. However, its performance is subject to data availability and generalizability.
5. Automated Brain Tumor Segmentation Using Cascaded Anisotropic Convolutional Neural Networks: Automated Brain Tumor Segmentation Using Cascaded Anisotropic Convolutional Neural Networks utilizes cascaded anisotropic CNNs to improve segmentation performance on the BraTS dataset. Yet, the model's computational overhead and sensitivity to tumor variations require further investigation for real-time application and generalizability.

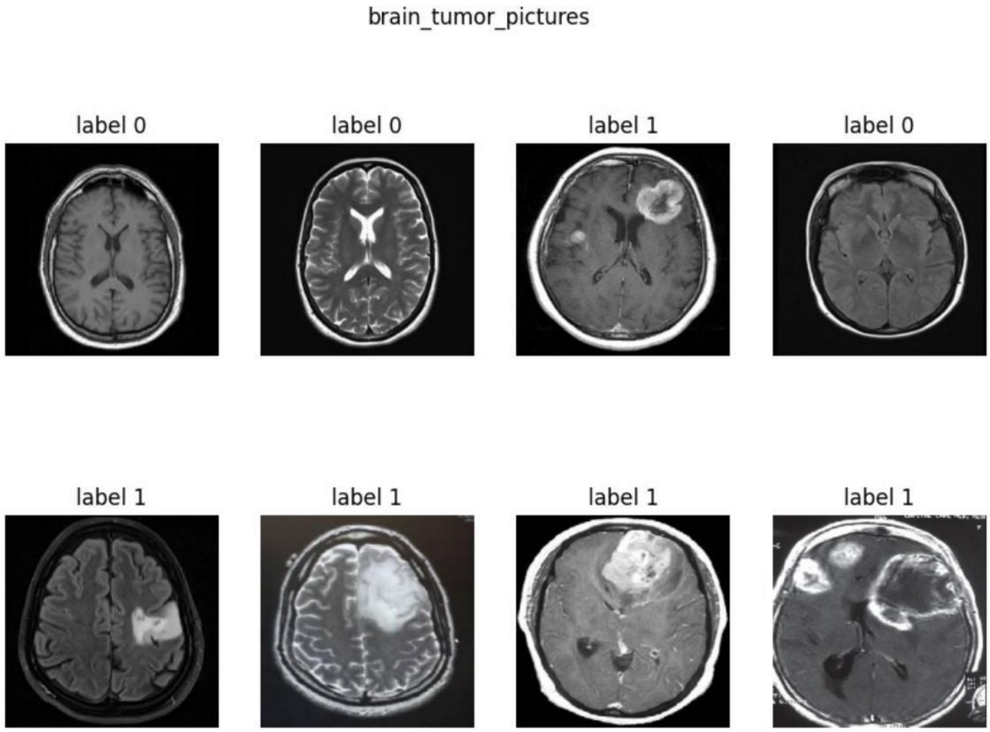


Figure 4: Sample 1 of Dataset

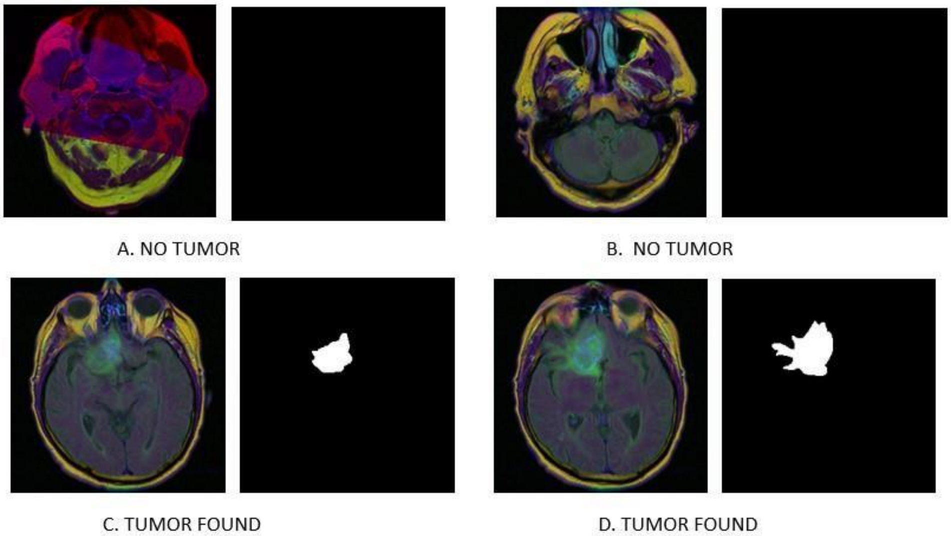


Figure 5: Sample 2 of Dataset

3.3. Preprocessing

In this section, the raw dataset goes through a cleaning process to make it in a format that can be used to train a machine learningmodel. Preprocessing is essentialfor preparing thedata for analysisand model training. Thefollowing are the essential phases in the data.

Preparation process: Data cleaning is the process of resolving missing numbers, getting rid of duplicates, and fixing any flaws or inconsistencies in the data. Depending on the degree of missingness and the effect on the dataset's integrity, missing values can either be imputed or eliminated from instances. Scaling and normalising the dataset to guarantee equal relevance and prevent the dominance of particular characteristics is necessary since the dataset may contain features with varying sizes and ranges. Common methods include standardisation (e.g., z-score normalisation) and min-max scaling (normalisation).

Data Privacy: In this proposed paper it was made sure that the dataset used complied with relevant privacy regulations and ethical consideration . The dataset was removed of any personally identifiable information to follow according to the data protection guidelines.

Class Imbalance Handling: A brain tumor dataset normally suffer from class imbalance due to tumor positive case being very few in number. In this paper techniques like under sampling, oversampling is used to balance the class and prevent the model from being biased .

Train-Test Split: In this proposed paper the dataset is divided in to training and testing set in order to properly and effectively evaluate the model's performance.

Brain Cancer Detection

We guarantee that the data is in an appropriate format for analysis and model training by preparing it in this way. This makes it possible to make precise and trustworthy model to detect brain tumor using an integrated strategy of objective measurements and subjective judgements.

3.4. Proposed Methodology

The proposed methodology involves the development of a customized CNN architecture and Inception v3 specifically designed for brain cancer and brain tumor detection. Although our dataset was limited to MR images, deep neural networks require a huge dataset to yield encouraging results. Our dataset contained 3900 MR images, with 85 percentage of the data utilized for training and 10 percentage and 5 percentage of the remaining pictures used for testing and validation, respectively. The amount of original data was expanded by augmentation so the training could then be enhanced. This also improves the model's learning capability. And as a result,the data was enhanced by duplicating the MRI images and applying rotation to it , width and height shifting, and zooming. After that, the datasets were verified using the holdout validation approach.For the proposed paper , It was crucial to select the optimum validation strategy for the dataset of 3900 scan pictures. We employed a holdout validation method, with most of the data used for training and only 15 percentage used for testing. The holdout validation strategy is the most often utilized and yields effective results. The holdout approach divides the dataset into two parts: a training set and a testing set, which allows the model to learn quicker. The deep learning model was trained using the training set, and its performance was evaluated using the testing set. And to evaluate the accuracy of the deep learning model and properly analyse the effectiveness of the model , some metrics were considered such as the accuracy, recall, and area under the curve (AUC).

Accuracy is the ability of an instrument to measure the accurate value. In other words, it is the the closeness of the measured value to a standard or true value. In this case it predicts the number of correct prediction by the proposed model divided by the total no of samples.

Accuracy =(TP ______ +$TNTP$

++$TNFP$ +FN)×100% where:

1. TP = True Positive
2. TN = True Negative

3. FN = False Negative
4. FP = False Positive

Recall is one of the another most important metrics to evaluate machine learning model. The recallcan be calculated as:

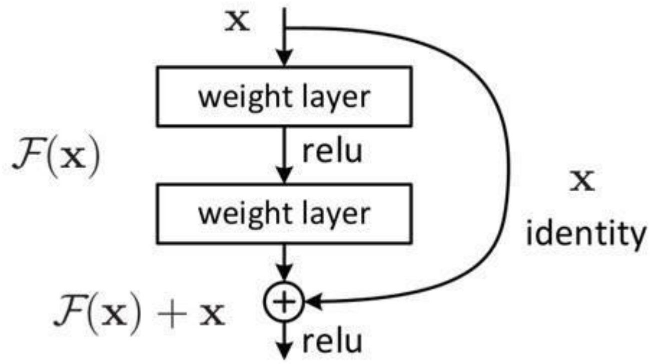
Recall = TP $TP{+}FN$

And last but not the least there is Area under the Curve , it evaluates exactly how efficiently and effectively the model distinguishes between both positive and negative . In this a higher AUC indicates a better performance by the model.

3.5. Deep Learning Models 1.

ResNet-50:

AlexNet earned top place in the LSVRC2012 classification challenge in 2012. Since then, ResNet has been the most intriguing thing to happen in the computer vision and deep learning worlds.Because of the foundation that ResNets provided, it was feasible to train extremely deep neural networks, which means that a network may have hundreds or thousands of layers and still function well.ResNets were first used to image identification tasks, but as stated in the study, the framework may also be utilized for non-computer vision activities to improve accuracy.



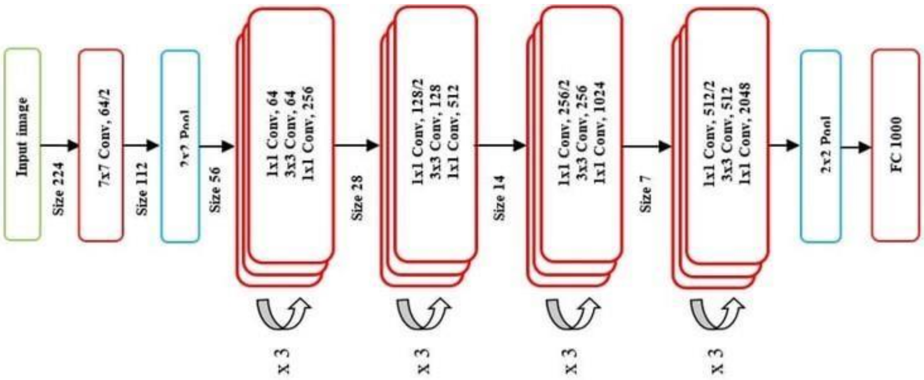
- This architecture can be used on computer vision tasks such as image classification, object localization, object detection.
- The framework can also be applied to non-computer vision tasks to give them the benefit of depth and to reduce the computational expense.

In this proposed paper, ResNet50 architecture will be utilized.

2. VGG19:

The architecture of VGG 19 is:

- A fixed size of (224 * 224) RGB image was given as input to this network which means that the matrix was of shape (224,224,3).



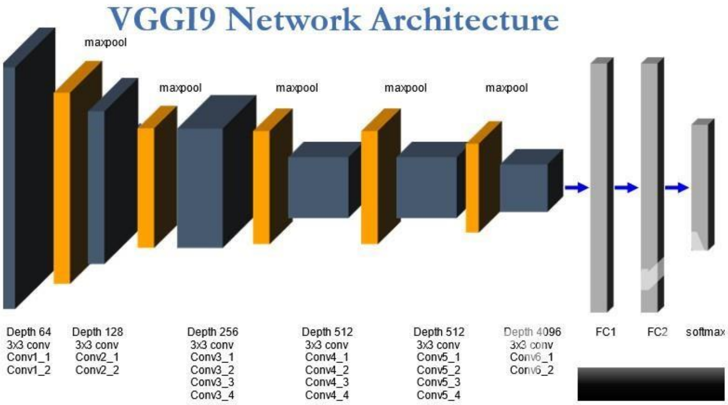
layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
		3×3 max pool, stride 2				
conv2_x	56×56	$\begin{bmatrix}3\times3, 64\\3\times3, 64\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 64\\3\times3, 64\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix}3\times3, 128\\3\times3, 128\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 128\\3\times3, 128\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix}3\times3, 256\\3\times3, 256\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 256\\3\times3, 256\end{bmatrix}\times6$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times6$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times23$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix}3\times3, 512\\3\times3, 512\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 512\\3\times3, 512\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				

- The only preprocessing that was done is that they subtracted the mean RGB value from each pixel, computed over the whole training set.
- Used kernels of (3 * 3) size with a stride size of 1 pixel, this enabled them to cover the whole notion of the image.

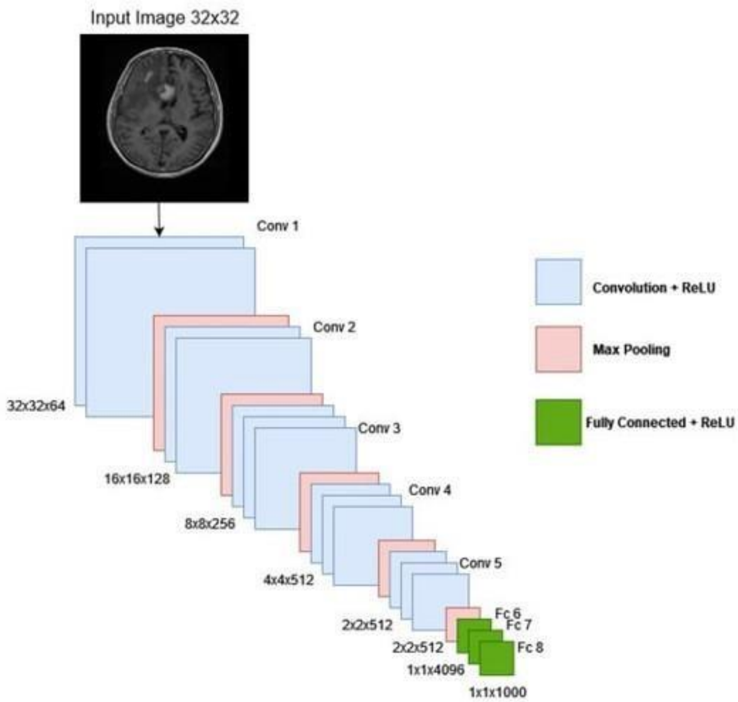
ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

- Spatial padding was used to preserve the spatial resolution of the image.
- Max pooling was performed over a 2 * 2 pixel windows with sride 2.

- This was followed by Rectified linear unit(ReLu) to introduce non-linearity to make the model classify better and to improve computational time as the previous models used tanh or sigmoid functions this proved much better than those.



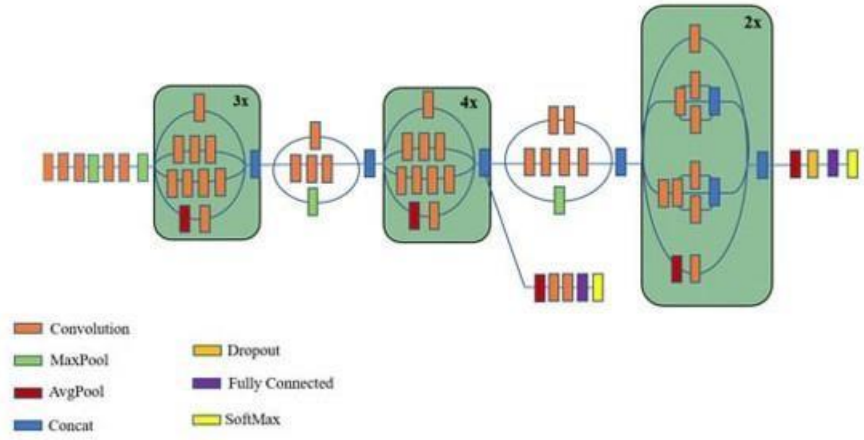
- Implemented three fully connected layers from which first two were of size 4096 and after that a layer with 1000 channels for 1000-way ILSVRC classification and the final layer is a softmax function.



3. INCEPTION V3:

   The Inception v3 model is a deep learning network model used mostly for picture categorization and detection.With a modest computer configuration, training Inception V3 is tough; it might take several days to train the model. Inception V3 is an improvement on Inception V1, which was launched by Google in 2014.

Inception V3 was published in 2015, with 42 layers and lower mistake rates than its predecessors. Convolution, pooling, dropout, fully connected, and softmax are the steps in the Inception process.



3.6. Result Analysis

The results of various types of developed deep learning models—i.e., the VGG16, CNN, ResNet-50, and Inception V3 classification algorithms—on the brain tumor MR image dataset are analyzed in Table given below, and comparisons are shown in Figure Below. In Table , we present the performance of the models with respect to the accuracy, area under the curve (AUC), recall, and loss function results. After analyzing the methods of the CNN, VGG16, ResNet-50, and Inception V3, it was observed that the CNN outperformed the other deep learning models based on the findings in Table . The CNN achieved a validation accuracy of 93.3 percentage, a validation AUC of 98.43 percentage, a validation recall of 91.1 percentage , and a validation loss of 0.260.

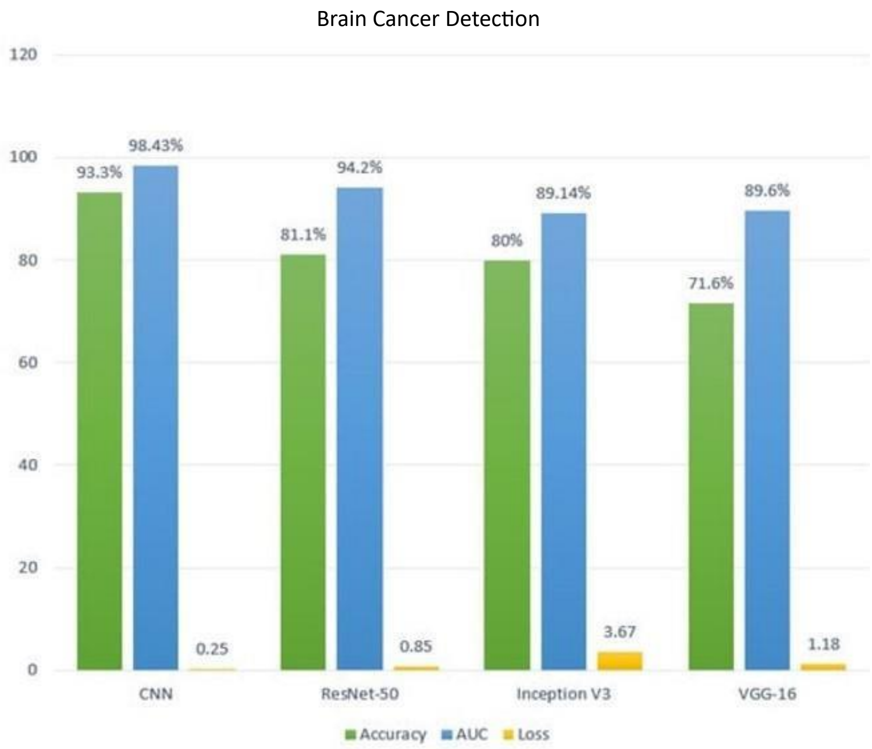


Figure 6: Performance analysis of the proposed model in terms of the accuracy, AUC, and loss

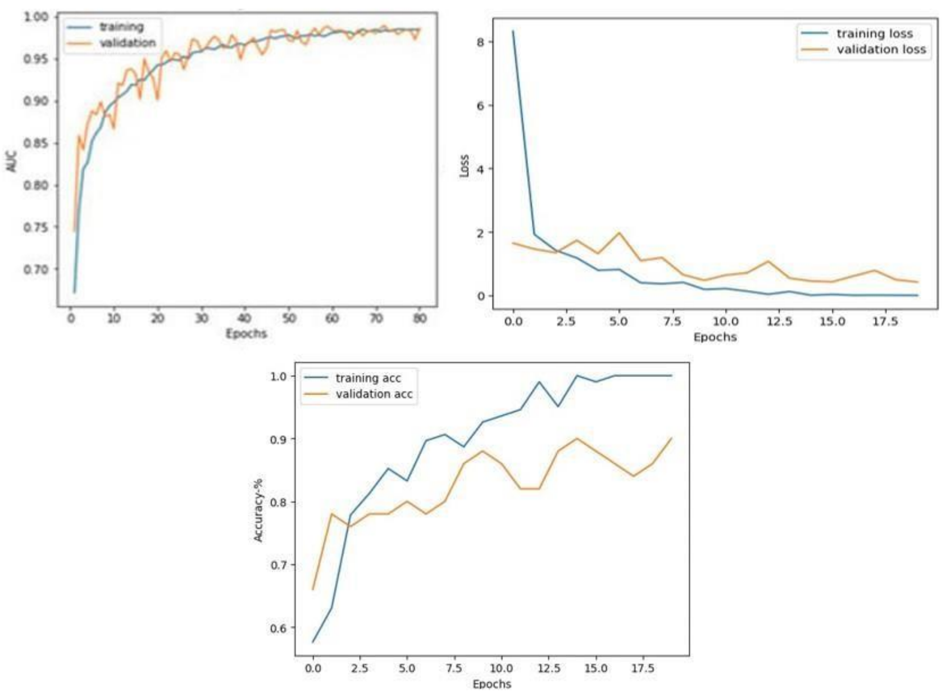


Figure 7: Graph representation of CNN (Accuracy,Loss,AUC)

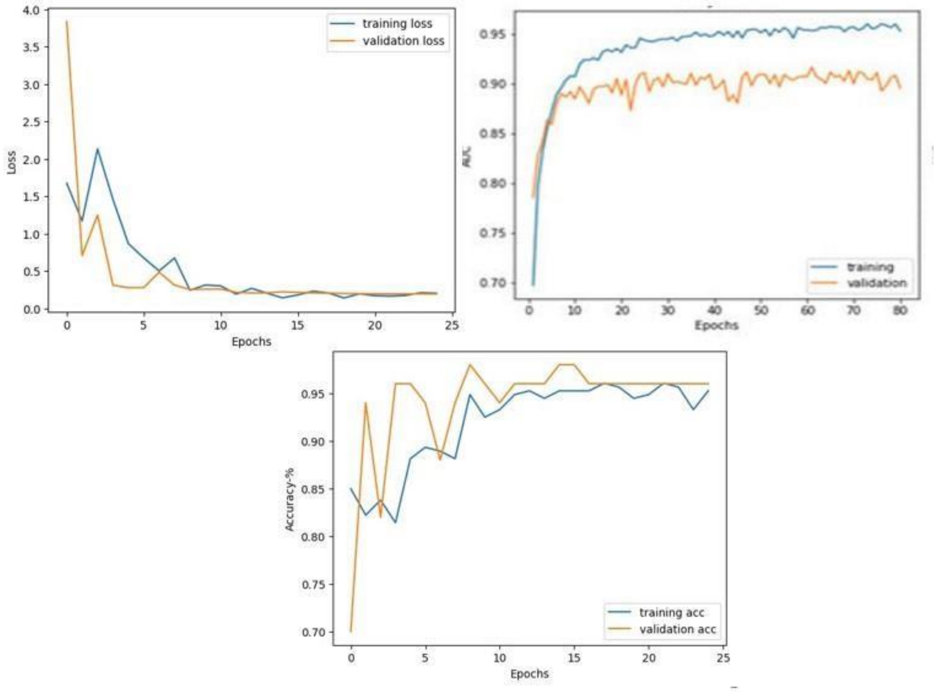


Figure 8: Graph representation of VGG19 (Accuracy,Loss,AUC)

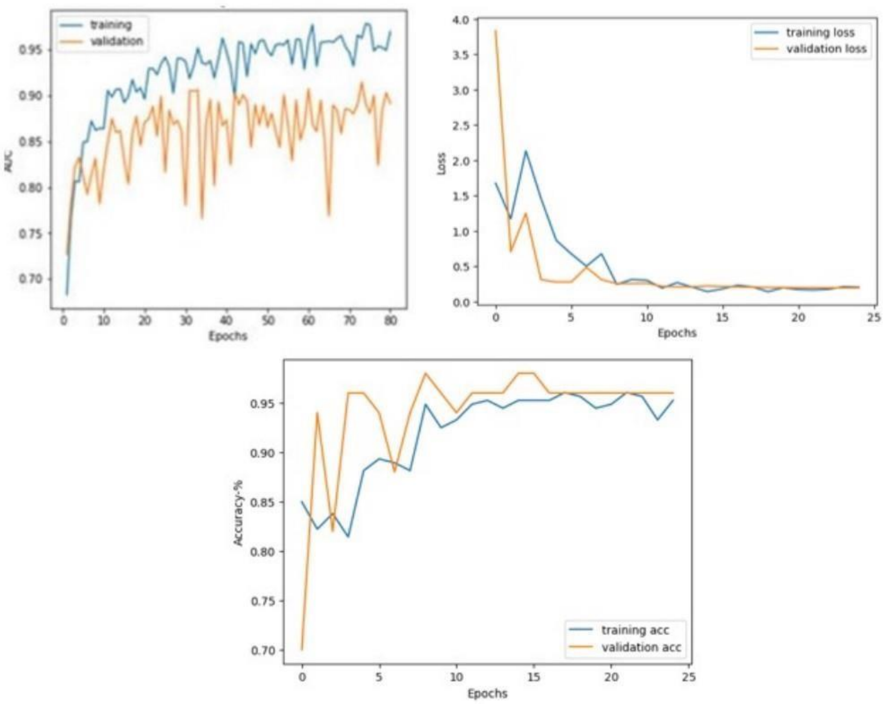


Figure 9: Graph representation of InceptionV3 (Accuracy,Loss,AUC)

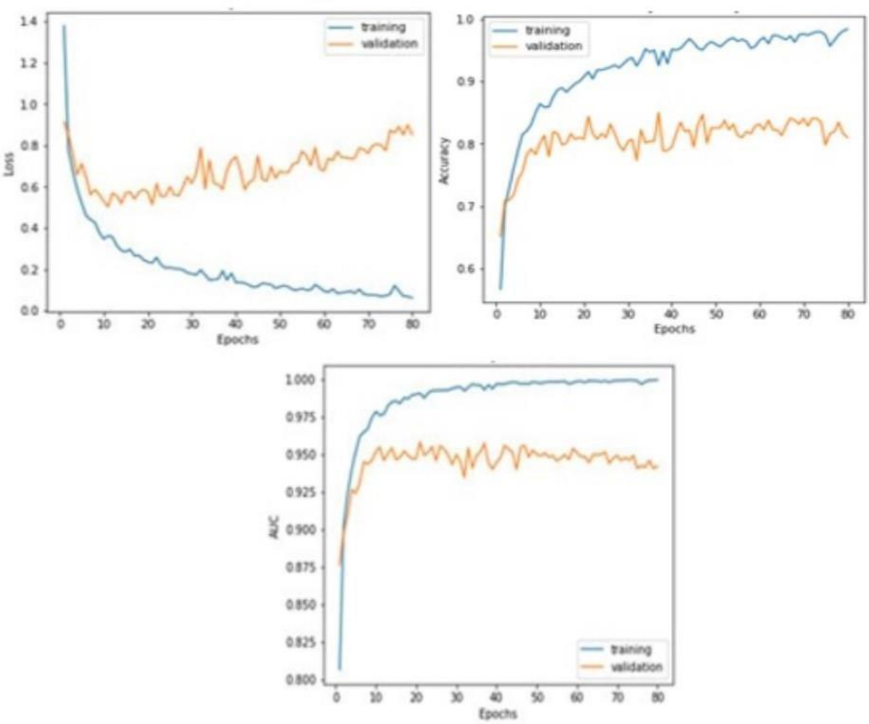


Figure 10: Graph representation of ResNet-50 (Accuracy,Loss,AUC)

Actual Class	
0	1

Brain Cancer Detection

Predicted Class	0	18	1
	1	1	30

Table 1
Confusion Matrix for InceptionV3

Class	Precision	Recall	F1-Score	Support
0	0.95	0.95	0.95	19
1	0.97	0.97	0.97	31
accuracy	-	-	0.96	50
macro avg	0.96	0.96	0.96	50
weighted avg	0.96	0.96	0.96	50

Table 2
Classification Report for InceptionV3

		Actual Class	
		0	1
Predicted Class	0	16	3
	1	1	30

Table 3
Confusion Matrix for VGG19

Class	Precision	Recall	F1-Score	Support
0	0.84	0.94	0.89	17
1	0.97	0.91	0.94	33
accuracy	-	-	0.92	50
macro avg	0.90	0.93	0.91	50
weighted avg	0.93	0.92	0.92	50

Table 4
Classification Report for VGG19

The above confusion matrix and classification report are based on the analysis conducted using a specific dataset. It’s important to note that these metrics are specific to the dataset and model used in this analysis and may not generalize to other datasets or models.

4. Discussion

For InceptionV3, The provided confusion matrix and classification report are indicative of a well-performing model, particularly for the InceptionV3 architecture. The confusion matrix indicates that out of the 50 samples, 18 instances of class 0 were correctly predicted, with 1 instance being incorrectly classified as class 1. Similarly, for class 1, 30 instances were correctly predicted, with 1 instance being incorrectly classified as class 0. This shows a high level of accuracy in the model’s predictions, with only a few misclassifications. Looking at the classification report, we see that the model achieved high precision, recall, and F1-score for both classes 0 and 1. For class 0, the precision, recall, and F1-score are all 0.95, indicating that the model’s predictions for class 0 are highly accurate and reliable. Similarly, for class 1, the precision, recall, and F1-score are all 0.97, showing the model’s effectiveness in predicting class 1 instances. Overall, the model achieved an accuracy of 0.96, indicating that it correctly classified 96 percentage of the samples. The macro-average and weighted-average metrics for precision, recall, and F1-score are all 0.96, further demonstrating the model’s strong performance across both classes.

In case of VGG19, the provided confusion matrix and classification report are indicative of a well-performing model, particularly for the VGG19 architecture. The confusion matrix indicates that out of the 50 samples, 16 instances of class 0 were correctly predicted, with 3 instances being incorrectly classified as class 1. Similarly, for class 1, 30 instances were correctly predicted, with 1 instance being incorrectly classified as class 0. This shows a high level of accuracy in the model's predictions, with only a few misclassifications. Looking at the classification report, we see that the model achieved high precision, recall, and F1-score for both classes 0 and 1. For class 0, the precision, recall, and F1-score are 0.84, 0.94, and 0.89, respectively. For class 1, the precision, recall, and F1-score are 0.97, 0.91, and 0.94, respectively. Overall, the model achieved an accuracy of 0.92, indicating that it correctly classified 92

5. Conclusion

In this research paper, we proposed a deep learning approach for the automated detection of brain cancer from MRI images. We highlighted the importance of MRI imaging in the diagnosis and treatment planning of brain tumors. Our study focused on the utilization of deep learning architectures, including ResNet-50, VGG19, and InceptionV3, for brain tumor detection. The dataset used consisted of 3900 MRI images, with a balanced distribution of cancerous and normal cases.

Through our comparative analysis, we found that the CNN model outperformed other deep learning models in terms of accuracy, AUC, and recall. The CNN model achieved a validation accuracy of 93.3

Our study contributes to the advancement of brain tumor detection technology, providing insights into the potential of deep learning techniques in medical imaging. The developed models can assist radiologists and clinicians in the early and accurate detection of brain tumors, leading to timely interventions and improved patient outcomes.

In conclusion, our research showcases the promising capabilities of deep learning in the field of medical imaging, particularly in the detection of brain tumors. Future research can focus on further refining the deep learning models, incorporating additional clinical data, and expanding the dataset to enhance the performance and generalizability of the models.

6. References

References have been taken from the following websites and papers:

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