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COMPARING DEEP LEARNING MODELS FOR 3D BRAIN TUMOR DETECTION

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ABSTRACT

A brain tumor is an irregular growth of cells within the brain. These growths can be either non-cancerous (benign) or cancerous (malignant). They may originate within the brain (primary tumors) or result from cancer cells spreading to the brain from other parts of the body (metastatic tumors). Brain tumor symptoms can vary depending on their size and location and may include headaches, seizures, personality changes, and neurological issues. Treatment options include surgery, radiation therapy, and chemotherapy, depending on the tumor's type and stage. Detecting and treating brain tumors early can significantly impact a patient's prognosis. Hence trusted and automatic classification schemes are essential to prevent the death rate of humans. Automatic brain tumor classification is a very challenging task in large spatial structural variability of the surrounding region of brain tumor. In this paper, we are provided with an overview of brain tumor detection using the deep learning Unet model. We used four types of Unet models 1. Unet model 2.ResUnet model 3. Resnext50Unet model 4. InceptionV3Unet model. The performance of the proposed model is measured and the result is compared with those of other approaches reported in literature. It is found that the proposed work is more efficacious than the state of art techniques.

Keywords: Deep Learning, Unet Model, Brain Tumor Detection, 3D Images, Health Care.

I. INTRODUCTION

In the human body brain is a complex organ whose weight is 3 pounds and this is a primary motor translator of the census and controller of behavior the source of all the traits that make up our humanity is the brain which is housed in a bone shell and protected by fluid.

Structure of the brain:- the brain is more likely a team of specialist all the components of the brain operates together they all have a unique role to play the forebrain midbrain and hindbrain are the three parts of the brain. The brainstem the cerebellum and the top portion of the spinal cord are all parts of the Hindbrain the hindbrain regulates breathing and heart rate with bodies essential processes.

The cerebellum organizes movement and learning repetitive moments like playing instruments are smashing tennis balls causing the cerebellum to fire. The midbrain is located at the top of the brainstem. Midbrain is responsible for reflex action and is a component of the circuit that regulates eye moment and other voluntary movements. The forebrain which is both a large and developed region is made up of the cerebrum and it lies beneath it.

Brain tumor:- excessive growth of brain cells or Cells close to brain tissues of the brain can develop brain tumors repeat pituitary gland, pineal gland, and membrane that's surrounded the surface of the brain are nearby structures brain tumors can start there.

Brain Tumors can be in the brain these are called primary Brain tumors sometimes cancer can spread under parts of the body it is also known as a secondary Brain Tumor or metastatic brain tumor. There are different types of primary brain tumors. Some brain tumors are noncancerous they are called noncancerous brain tumors or benign brain tumors. Noncancerous brain tumors may grow over time and press on the brain tissues. And cancer Brain Tumors also called malignant Brain Tumor grow quickly and destroy the brain tissues.

Brain Tumors can range in size from small to large. Some rain tumor is identified when they are very small because they show the symptom that you notice right away. Some Brain tumors can grow very large before they are found. Some part of the brain is less active than other parts of the brain. If a brain tumor starts in the less active part of the brain it will not cause any symptoms right away because it brain tumor size is grow quite large before it can be detected.

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Brain tumors are Detected by using MRI (magnetic resonance imaging) scan and CT (computed tomography) scan. This scan will show a brain tumor if it is present. MRI is the best way for looking brain and spinal cord and it is highly recommended in tumor areas the image we get from MRI is more detailed and clear than a CT scan.

Discussion of deep learning that has emerged in the medical sector, Whether deep learning is safe for the medical sector can Humans can rely on it? Because the medical sector is a very critical area where one mistake can take one life! so in this paper, we have research on Deep learning which is using CNN models to detect brain tumors using MRI scans.

Deep learning comes from machine learning. We can also say that deep learning is an updated version of machine learning and machine learning is the basics of deep learning. Deep learning is a technique that teaches computer human things. One of the key examples of deep learning is driverless cars. That enables them to recognize the stop signal or to distinguish pedestrians from a lamppost and it is also the key to voice control systems that are everywhere like phones, tablets, TV, etc. Deep learning is in the spotlight lately for good reason because it achieves a goal that was impossible before.

Deep learning uses various models to train the computer for classification tasks directly from images, text, or sound. Deep learning achieves the best out-of-best accuracy and sometimes exceeds the human level performance. Those models are trained by large sets of labeled data and neural network architecture that contain many layers.

In the healthcare sector, deep learning is used for analyzing the reports of MRI scans and other images to detect abnormalities. This doesn't replace the doctor but it enhances the speed of the doctor's work and takes less time. Because of it, the treatment of the patient will start sooner. This system works based on a deep neural network (DNN).

The experiment uses 3D Unet model on the BRATS dataset . A 3D U-Net model is a neural network designed for three-dimensional image data, especially useful in 3D medical image segmentation. It extends the U-Net architecture to work with 3D images, employing an encoder, a central bottleneck, and a decoder, with skip connections to maintain spatial information.

II. LITERATURE REVIEW

The major difficulty in brain tumor detection and classification is the appearance of the tumor region. The tumor region size, shape, location, and intensity vary from image to image for a particular type. Tonmoy Hossain1, Fairuz Shadmani Shishir. The authors discuss the challenges of manually detecting tumors and propose a CNN-based method that achieves 97.87% accuracy. They emphasize the importance of large and diverse datasets for training CNNs. CNNs have shown great promise in efficiently detecting brain tumors[1].

Masoumeh Siar & Mohammad Teshnehlab discuss the importance of early detection and treatment of brain tumors. The authors propose a new method that combines feature extraction with a convolutional neural network (CNN). The CNN was able to achieve an accuracy of 98.67% on the test data. This method outperforms other state-of-the-art methods[2].

Yakub Bhanothu, Anandhanarayanan Kamalakannan & Govindaraj Rajamanickam During their discussion, they explored the use of Faster R-CNN, a deep learning algorithm, for identifying and categorizing brain tumors. The algorithm underwent training with a dataset of more than 2,000 MRI images and achieved an average accuracy of 77.60%. This indicates that Faster R-CNN holds the potential as a reliable tool for detecting and classifying brain tumors[3].

Pranjal Agrawal, Nitish Katal, and Nishtha Hooda discuss the challenges of brain tumor detection and the importance of early detection. The authors propose a method using 3D U-Net and CNN models. They evaluate their method on a dataset of MRI images and achieve promising results[4].

J. Seetha and S. Selvakumar Raja discuss the challenges of brain tumor classification and state-of-the-art methods. The authors propose a new method based on convolutional neural networks that achieves high accuracy with low complexity. They evaluate their method on a dataset of brain tumor images and show that it outperforms other methods[5].

Amjad Rehman & Muhammad Attique Khan discuss the challenges of brain tumor diagnosis and the need for automated methods. The authors propose a new method using 3D CNN and feature selection. They evaluate their method on three BraTS datasets and achieve state-of-the-art results[6].

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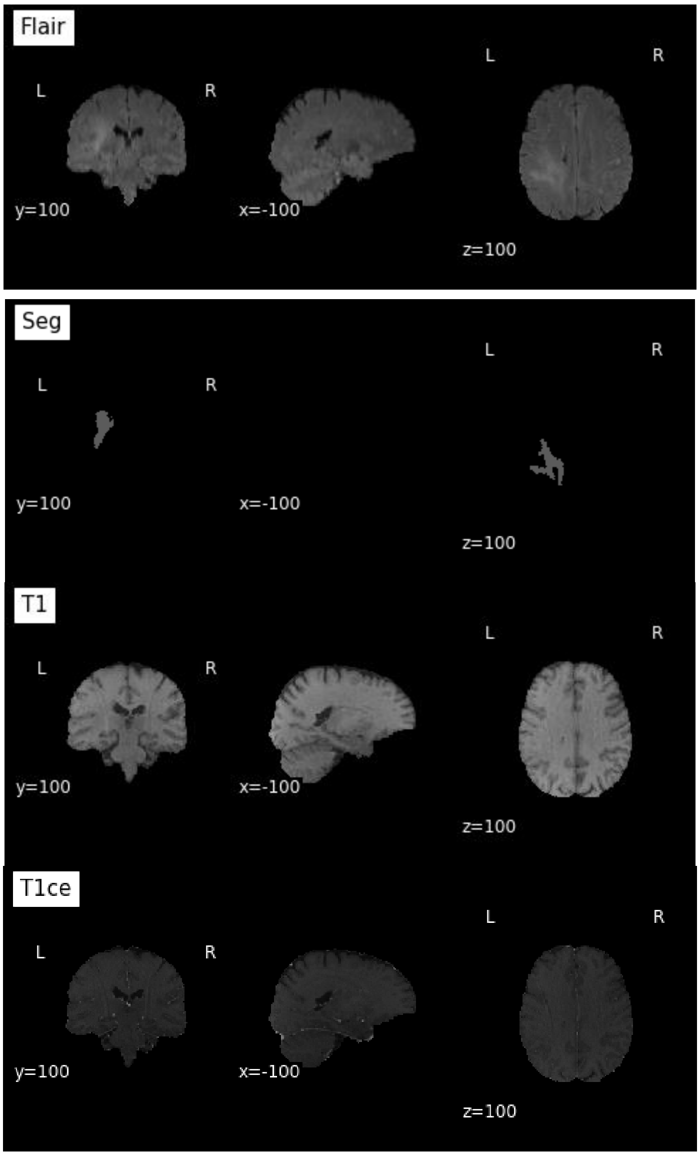
Sultan B. Fayyadh & Abdullahi A. Ibrahim propose a method for brain tumor detection and classification using CNNs and deep learning techniques. The method achieves an accuracy of 98.23% on the test dataset, which is higher than other state-of-the-art methods. The authors also discuss the importance of using a large and diverse dataset to train CNN models for brain tumor detection[7].

III. METHODOLOGY

Dataset :

In multimodal magnetic resonance imaging (MRI) scans, BraTS has always concentrated on evaluating cutting-edge techniques for brain tumor segmentation. BraTS 2020 segments intrinsically heterogeneous (inappearance, shape, and histology) brain tumors, such as gliomas, using multi-institutional pre-operative MRI scans. BraTS'20 also uses integrative analyzes of radiomic features and machine learning algorithms to pinpoint the clinical validity of this segmentation task, as well as estimate patient overall survival and the discrepancy between faux progression and actual tumor recurrence. Finally, BraTS'20 attempts to evaluate the algorithmic sophistication of tumor segmentation.[4]The dataset includes images from multiple MRI modalities: T1, T1CE, T2, and FLAIR. These provide complementary information for accurate tumor segmentation and diagnosis.



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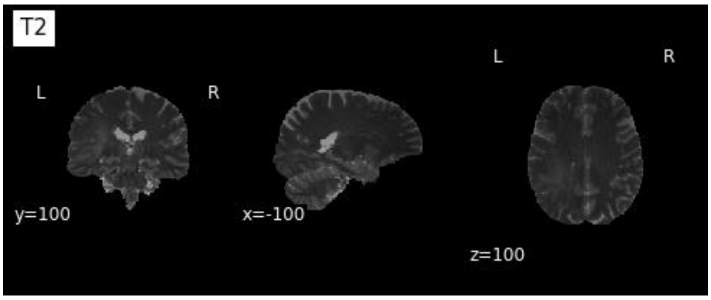

Figure 1: Images of Dataset

3D-UNET:

The 3D U-Net is a neural network architecture designed for 3D medical image segmentation, particularly in applications such as brain tumor detection. It is an extension of the traditional 2D U-Net for processing 3D data. The network is made up of an encoder-decoder structure with skip connections that help to preserve spatial information. The encoder reduces the spatial dimensions, and the decoder then up samples the feature maps to produce a segmentation map. This architecture is highly effective for accurately segmenting structures in 3D medical images, such as tumors, organs, or other regions of interest,

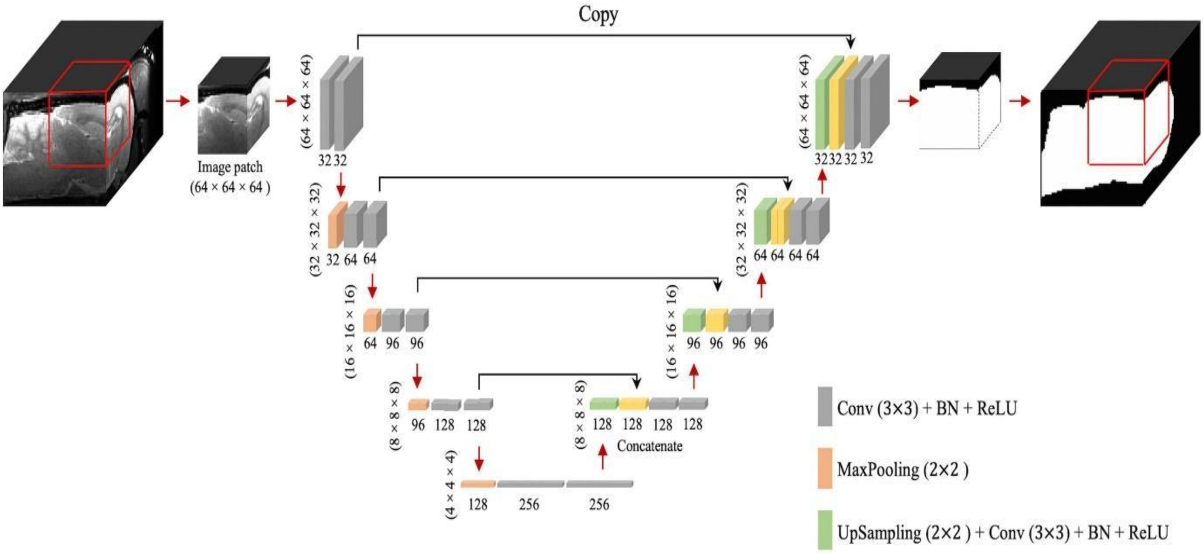

Figure 2: 3D Unet Structure

IV. PROPOSED SEGMENTATION MODEL

In this proposed work 4 models are used 1. 3D-Unet, 2. ResNext Unet, 3. ResUnet, 4. Inception Unet.

1. Proposed 3D- Unet architecture

Contraction Path (Encoder):

- The network starts with the contraction path, which is responsible for capturing features and reducing the spatial dimensions of the input volume.
- It consists of a series of 3D convolutional layers (Conv3D) with ReLU activation functions and dropout layers (Dropout) to prevent overfitting.
- Max-pooling layers (MaxPooling3D) downsample the feature maps at each step, reducing the spatial dimensions and increasing the receptive field.
- The number of filters in each convolutional layer typically increases as you go deeper into the encoder (c1 to c5), allowing the network to capture more complex features.

Expansive Path (Decoder):

- The expansive path takes the contracted feature representations and reconstructs the segmented output.

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- It uses 3D transpose convolutional layers (Conv3DTranspose) to upsample the feature maps, essentially performing the reverse operation of max-pooling.
- Concatenation layers (concatenate) combine the upsampled features with corresponding features from the contraction path to provide skip connections. These connections help preserve spatial information and enhance segmentation accuracy.
- Similar to the contraction path, the decoder consists of convolutional layers with ReLU activation functions and dropout layers (c6 to c9).
- The final layer uses a 3D convolutional layer with a softmax activation function to produce the segmentation map with four channels, typically representing different classes or labels

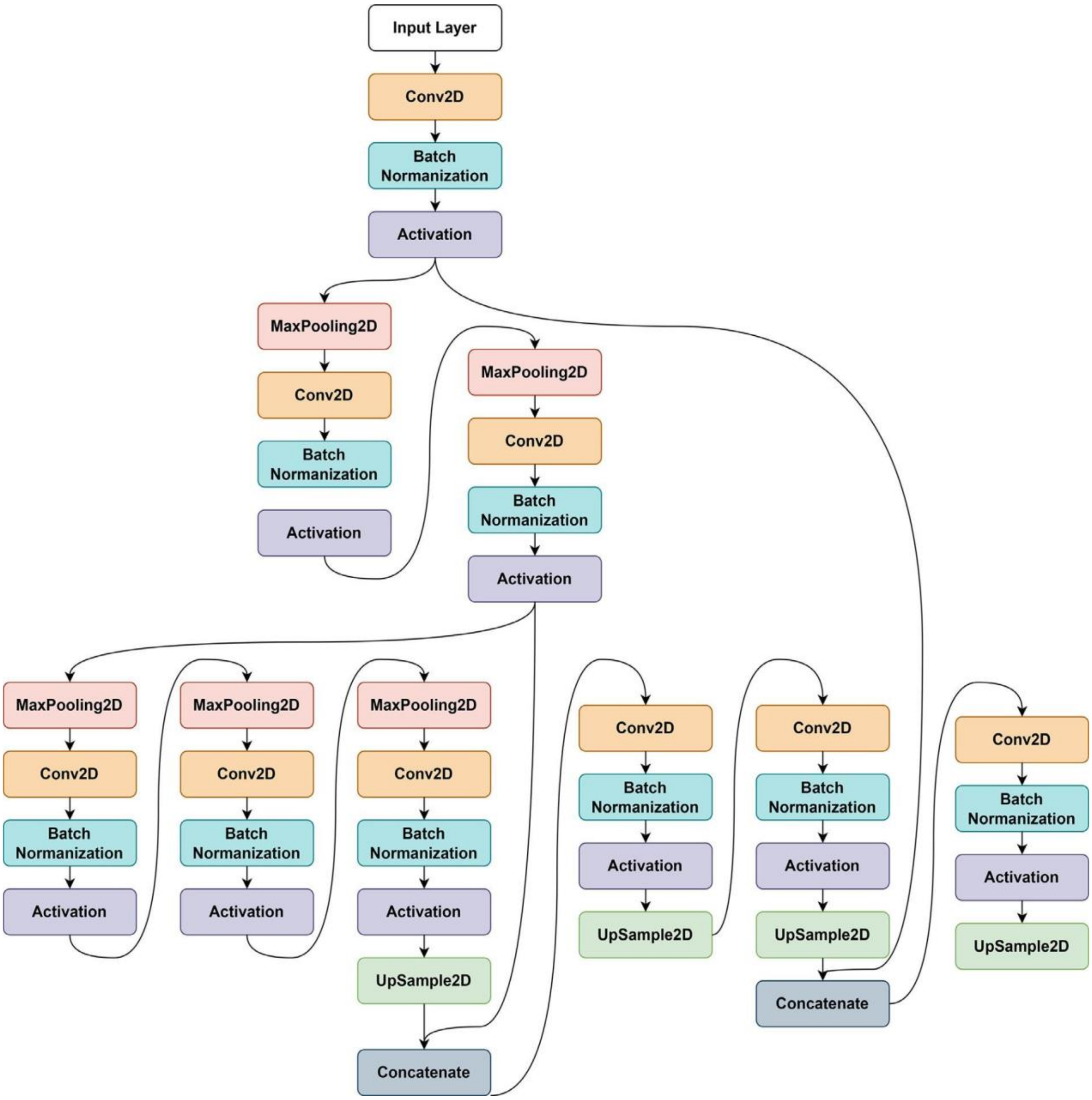

Figure 3: Segmentation and Detection model

2. Proposed ResNext50 Unet architecture

The "ResNext-50 U-Net" architecture combines ResNext-50, known for its deep feature extraction, with the U-Net, a popular segmentation network. ResNext-50 extracts high-level features, while the U-Net's decoder refines spatial information for accurate segmentation. Skip connections link the two parts, enabling the network to blend rich features with fine spatial details for tasks like medical image segmentation.

3. Proposed ResUnet architecture

ResUNet is a hybrid neural network architecture that combines the powerful feature extraction capabilities of ResNet with the precise spatial information preservation of U-Net. It's widely used for image segmentation tasks, such as medical image segmentation, and excels at combining high-level features with fine spatial details for accurate segmentation.

- The network starts with an input layer that takes images of size 240x240 pixels with a single channel (grayscale).
- It then proceeds with multiple convolutional layers and batch normalization layers. Convolutional layers are used to extract features from the input image.
- The network includes residual connections (the "add" operations), which help in mitigating the vanishing gradient problem and allow the network to learn better.
- As you move through the layers, the spatial dimensions of the feature maps change, usually halving after pooling layers.
- Finally, it appears to be performing up-sampling and concatenation operations to combine high-level and low-level features, which is common in U-Net architectures for segmentation tasks.
- The last layer seems to be producing a 1-channel output with a single filter. This final output could be interpreted as a probability map for binary image segmentation, where each pixel indicates the probability of belonging to a specific class (typically, object vs. background).

4. Proposed InceptionV3 Unet architecture

The "InceptionV3 U-Net" architecture combines the InceptionV3 neural network for feature extraction with the U-Net architecture for image segmentation. It uses InceptionV3 to capture image features and then employs U-Net's decoder to create detailed segmentation maps. This hybrid architecture is effective for tasks like image segmentation and object detection.

- **Backbone Selection**: The code specifies 'InceptionV3' as the backbone network for feature extraction. This backbone is a pre-trained neural network, which is widely used in image-related tasks.
- **Preprocessing**: The code uses the 'preprocess_input' function to apply preprocessing to the input data, which is often required for neural networks, particularly when using pre-trained models.
- **Model Configuration**: The U-Net model is created using the sm.Unit function. It is designed for binary image segmentation (e.g., segmenting objects from the background). The sigmoid activation function is used to produce pixel-wise binary predictions.
- **Encoder Weights**: The 'encoder_weights' parameter is set to None, meaning the weights of the InceptionV3 backbone won't be loaded. The model will be trained from scratch.
- **Encoder Freeze**: The 'encoder_freeze' parameter is set to True, which means the weights of the InceptionV3 backbone will be frozen during training, and only the U-Net part of the network will be trained.
- **Optimizer**: The Adam optimizer is chosen with a learning rate of 0.001. This optimizer is commonly used for training neural networks.
- **Loss Function**: The loss function used is a combination of binary focal loss and dice loss, which are suitable for binary image segmentation tasks. Combining losses this way can lead to more robust training.
- **Metrics**: The code specifies two evaluation metrics: Intersection over Union (IoU) and F1 score. These metrics are used to assess the quality of the segmentation results.

V. RESULTS AND DISCUSSION

For performance evaluation of our proposed model we used BRATS 2020 dataset. All the images are MRI image from different modalities like - T1, T2, FLAIR, Seg and T1ce. We divide the dataset in training and testing in 80 and 20. To justify our proposed model steps of segmentating the tumor of 3D brain tumor MRI is illustrated and comparatively analyse of proposed model of classification using deep learning is shown we got 97.83% in Unet model, 98.12% in ResUnet model, 98.56% in ResNext50-Unet model, 99% InceptionV3-Unet model.

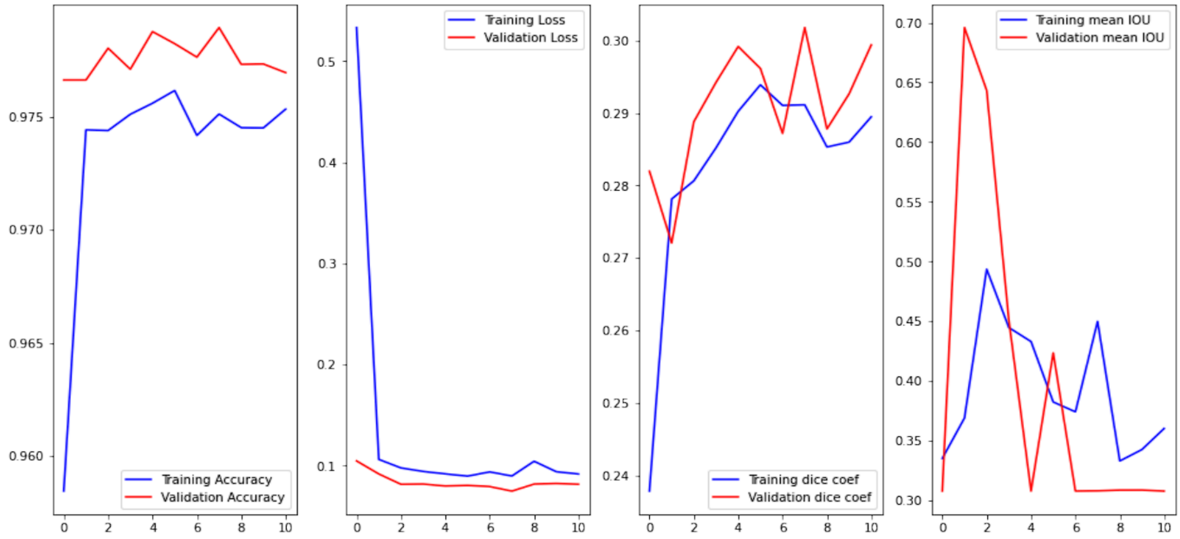

Figure 4: Unet Model Accuracy, Loss, Dice Coefficient, Mean IOU

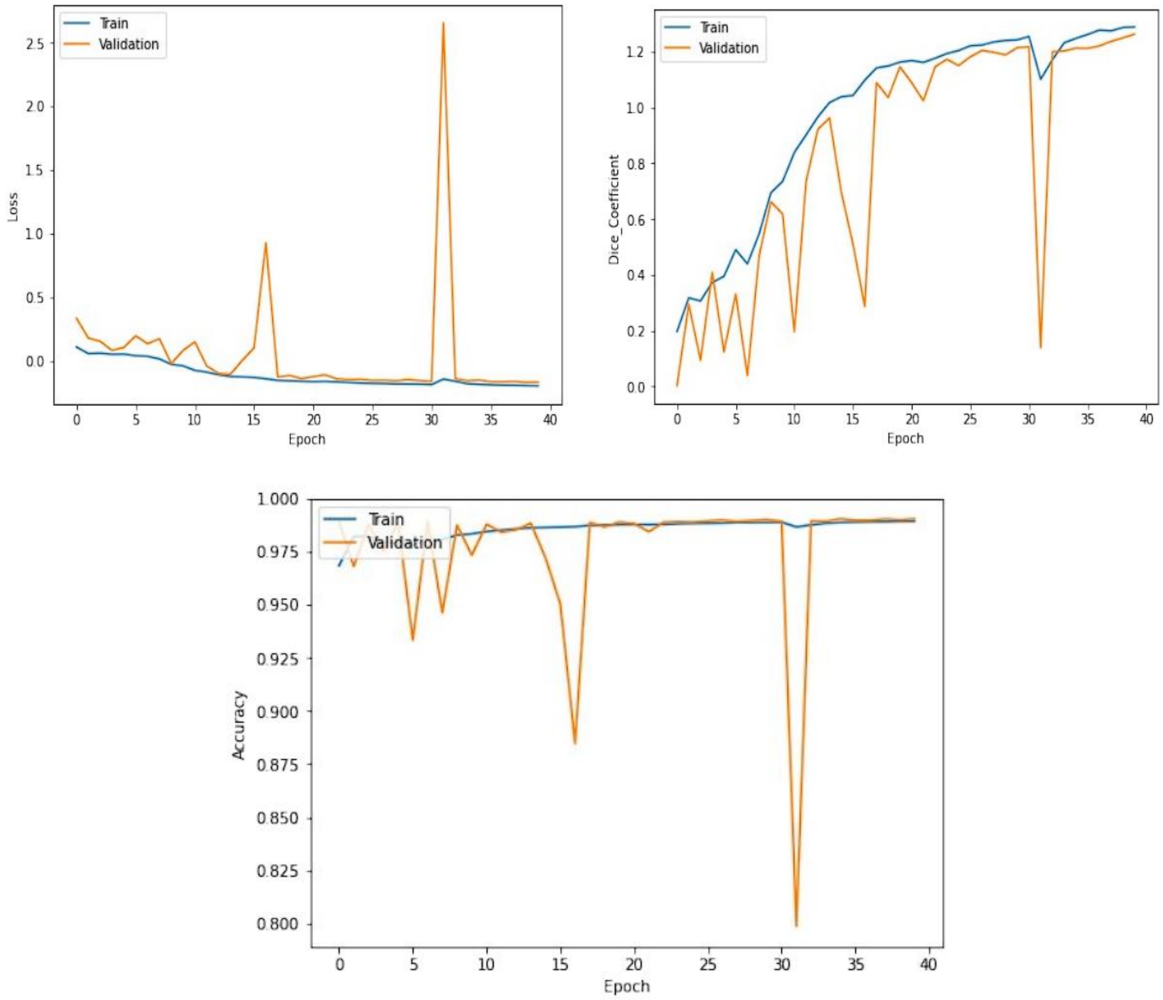

Figure 5: ResUnet Model Accuracy, Loss, Dice Coefficient

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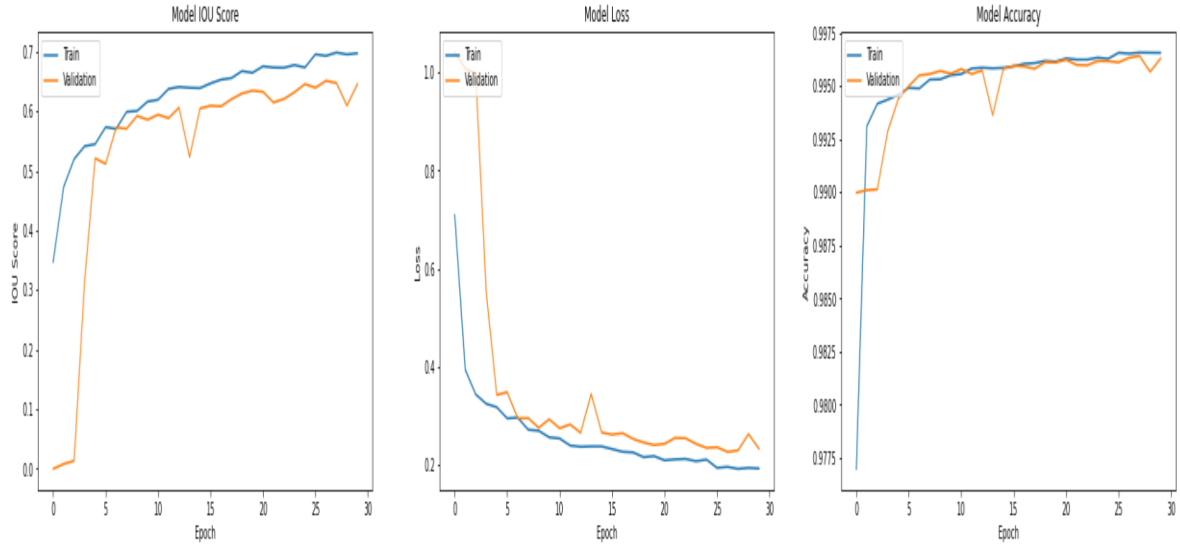

Figure 6: ResNext50-Unet Model Accuracy, Loss, Model IOU Score

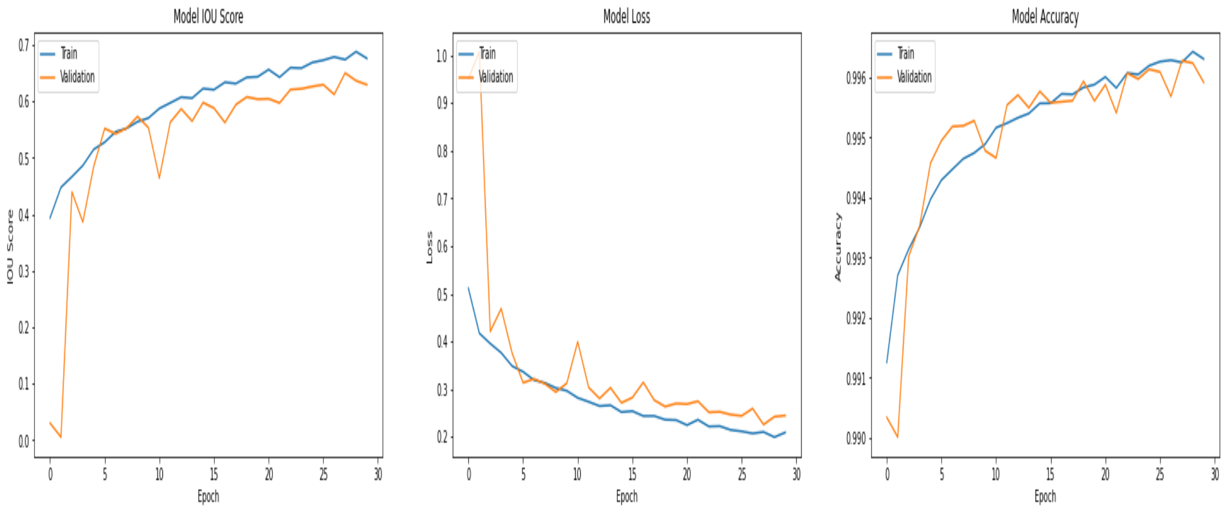

Figure 7: InceptionV3-Unet Model Accuracy, Loss, Model IOU Score

Table 1: Accuracy Table

Models	Accuracy
Unet Model	**97.83%**
ResUnet Model	**98.12%**
ResNext50-Unet Model	**98.56%**
InceptionV3-Unet Model	**99%**

VI. CONCLUSION

This paper discuss about the automatic brain tumor detection of MRI images using deep learning algorithm the four types of algorithm are used 1. Unet Model, 2. ResUnet Model, 3. Res next50-Unet Model, 4. inceptionV3-Unet Model. The study utilized deep neural networks to segment and detect brain tumors. The MRI image dataset was used to train the neural network, and the segmented model was evaluated using the soft dice loss function. The model was then trained to correct the losses and produce the segmented image as output. To pass through the segmentation model, the 3D MRI model was divided into 3D sub-models. Two datasets were used for the CNN models, each taken from different patients from different parts of the world to improve generalization. The CNN model was implemented specifically for the three most common types of brain tumor:

glioma, meningioma, and pituitary. This allowed for immediate classification without the need for area-based pre-processing procedures. The results of the study demonstrate the effectiveness of the proposed model when compared to existing models in the literature[4].

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