DETERMINATION OF AREA OF THE TUMOR WITH DEEP LEARNING TECHNIQUES

N. Phani Bindu[1], P.Narahari Sastry[2]
[1] *Research Scholar, Dept. of E.C.E, Osmania University, Telangana, India.*
[2] *Professor, Dept. of E.C.E, CBIT Gandipet, Telangana, India.*

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U-Net, Modified U-Net, ResNet50, Dice Coefficient, Encoder, Decoder

ABSTRACT

In the realm of medical imaging, tumor identification and categorization are crucial for a variety of reasons. First and foremost, effective cancer treatment and management depend greatly on a prompt and accurate tumor diagnosis. The recommended therapy will be very effective due to the early tumor discovery, and there may be a chance of increase in the patient's survival rate. The clinical professionals can access the tumor's size, form, and location with the tumor segmentation method. This information will be very crucial for planning the better treatment which may include surgery, radiation therapy or chemo therapy. The tumor's stage can be determined by computing the tumor's area. Patients may experience variations in the tumor's minute characteristics as well as variations in tumor size. In some cases an MRI picture of the cerebral fluid may also appear as a mass of tissue. The identification of the smallest tumor along with the minute details of the tumor is required to be obtained from the image and this can be obtained using U-Net which is used for semantic segmentation. The Modified U-Net using ResNet models are employed for the smallest area calculation and the tumor as small as 105 pixels is obtained using this method. These small tumors are less likely to create visible symptoms and may not even show up on conventional imaging methods until they are greatly expanded in size. The Modified U-Net with ResNet as encoder and decoder are employed for the tumor area calculation by which the patient can undergo effective treatment and improve prognosis.

Introduction

Early identification of tumor is essential for effective treatment and management of tumors. It is essential for an algorithm to identify both small and big tumors. In the case of cancer screening, detecting smaller area tumors is of special focus as they are harder to detect compared to big tumors because they are less likely to create visible symptoms and may not be shown up on conventional imaging methods until they are greatly expanded in size. Smaller tumors are often more amenable to therapy than bigger ones and finding a tumor at early stage might improve a patients odds of undergoing effective treatment and also improve overall prognosis. Bigger tumors are simpler to find, but by the time they are discovered there may be a chance of these tumors to spread to other parts of the body. A delayed diagnosis may also result in therapies that are more invasive and aggressive and also decrease the survival rate. So it is necessary to design an algorithm to detect both small and big tumors with high level of precision by which it is able to detect big tumors before they develop and spread and this may also allow early identification and treatment for small cancers. This has lead to the development of therapies that are more focused and effective and also novel technologies for early identification and prevention of the disease.

In medical imaging, tumor identification and categorization are crucial for a variety of reasons. First and foremost, effective cancer treatment and management depend greatly on a prompt and accurate tumor diagnosis. The recommended therapy will be very effective due to the early tumor discovery, and there may be a chance of increase in the patient's survival rate. The clinical professionals can access the tumor's size, form, and location with the tumor segmentation method. This information will be very crucial for planning the better treatment which may include surgery, radiation therapy or chemo therapy. The two main important points to be considered in the tumor segmentation process are first monitoring the development of the disease and secondly how effectively the applied therapy is working. The segmentation of tumor is an essential step in the discovery and development of novel cancer therapies. The correct segmentation of the tumor may help the researchers to identify the potential bio-markers, doing research in the fundamental biology of cancers and creating novel treatments that are used to treat certain types of cancer subtypes.

The segmentation of brain tumor size manually using 2D MRI images is a laborious and error-prone process, where the proficiency of the clinical expert is crucial to get accurate output. In this regard, obtaining an accurate measurement of the tumor size requires a consistent, and complete automated segmentation approach for the detection and segmentation of the brain tumors

Review of Literature

To determine the stage of the cancer growth, two different types of tumors are to be taken into consideration: primary tumors and secondary tumors. It is possible for both primary and secondary cancers to grow **Lin *et al.*, (1991) [1].** The wide range of imaging modalities and techniques allows a precise diagnosis **Das (2016) [2]** of the brain malignancies. The MRI sequences may be used to investigate stroke lesions **Mohan and Subhasini (2018) [3],** depending on several criteria like the patient's age, the location and severity of the tumor, and others **Isin *et al.*, (2016) [4].**

In any semantic segmentation network, UNET is one of the approaches that are frequently employed. Specifically, it is a fully convolutional neural network (CNN) designed to learn from less training samples. It is an improvement over **Evan Shelhamer and Jonathon Long (2017) [5]** fully connected network (FCN), which was developed for semantic segmentation and this design concept is known as UNET. Its architecture is in the shape of a ‘U’ and consists of the blocks of encoder and decoder having a bridge connection in between. The encoder network contracting route reduces the size of each encoder block by half, and increases the number of filters which are also referred to as feature channels by two. In a similar way, the decoder network reduces the number of feature channels by one while concurrently increasing the spatial dimensions by a factor of two.

An up sampling method is required for increasing the grid size by which the produced picture image may be the same size as the input or it may be slight bigger. For this reason the network topology is considered in a U-form, by which the name U-Net is proposed. In sampling and decoder routes a series of transposed convolutions are used in which pixels between and around the pixels which are present are added. The process of up sampling is nothing but operating in reverse to the down sampling approach.

When the output must have a comparable size to the input and the same degree of spatial resolution as the input, U-Nets can be a very useful tool in problem solving. When images are classified using convolutional neural networks, a series of stride two convolutions is used to first classify the image into one or more classes and with each iteration of the process, the grid size gets reduced.

In order to increase the grid size and produce an image that is either the same size as the original image or larger, an up sampling approach is required. Because of this, the network's topology assumes the shape of a U, hence the name U-Net. The path employs up sampling and decoders on the right side of the U and down sampling and encoders on the left. A sequence of transposed convolutions is carried out for upsampling and decoding, adding pixels between and around the pixels that are already present in each case. One way to think about the down sampling process is as an opposite of the upsampling strategy.

The area is the no. of pixels in the image i.e. the pixels having the intensity level (white) represents the tumor region by **Hunnur Shrutika Santosh *et al.*,(2017) [6]**. It is among the most crucial parameters for determining a tumor patient's stage. One typical element thought to confront the problem of a vanishing gradient in classic neural networks is the training process **Chen *et al.*, (2018) [7]**. In fact, the difficulty where the gradient norm of previous layers is lowered to zero during the training phase is what characterizes this issue. An adaptation of the Residual Network (ResNet) technique is made to address this issue **Kumar *et al.*, (2021) [8].**

Each residual layer's output in a ResNet is connected to its input, creating a connection that serves as the layer's subsequent input to be demonstrated. A U-shaped structure is created as a result of the contracting path's symmetry with the growing path. The network operates within each convolution's valid zone and doesn't use any tightly connected layers. **Chen *et al.*, (2018) [7]** presented an improved U-net architecture with residual blocks in a more recent development. An enhanced deep learning model for brain tumor classification from MRI images using Residual Network (ResNet), **Sarah *et al.*, (2020) [9]** a type of deep learning architecture is used for the classification of brain tumors.

ResNet is a novel architecture that was announced in 2015 by the researchers at Microsoft research center and named as ResNet. It is a short form of residual network. This network introduced a notion named as residual blocks in order to overcome the issue of exploding or vanishing gradient which has been experienced in the network. This network particularly uses the advantage of skip connections. Activations on one network are connected to the other network by skipping connections which bypasses the middle layers which results in the formation of a residual element. The ResNet formation involves the stacking of these residual blocks successively.

METHODOLOGY

Proposed U-Net Architecture using Deep Learning ResNet50 model

Network architecture of U-NET

U-Net is a type of Convolutional Neural Network design designed for biomedical image segmentation. These U-Nets are very helpful in solving problems where the output must be in comparable in size to the input and also has the same degree of spatial resolution as the input. The image is initially taken and then down sampled using convolutions, with the grid size getting smaller with each iteration, in order to use CNN for image classification.

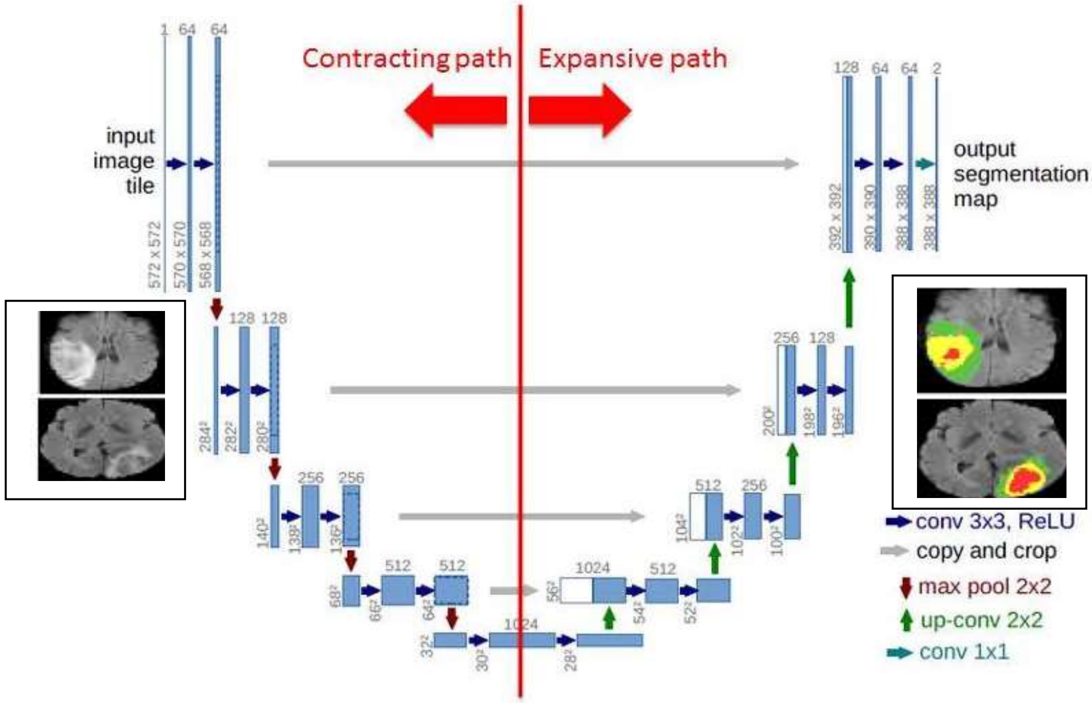


Figure 3.1: Architecture of U-Net

Blocks of U-Net Architecture

- **Encoder** – This performs the function of a feature extractor and moves through a series of encoder blocks. The ReLU activation function brings non-linearity which aids to generalize the training data. It has 2x2 max pooling layers to down sample in between with a stride of 2. In this the Channels are doubled with convolution after max pooling.
- **Skip Connection –** It is provided for matching the decoder block at the output of ReLU.
- **Decoder** - It has a repeated 3x3 convolutional and ReLU layers. It does the process of upsampling followed by 2x2 convolutional layers. The channels are halved after upsampling convolution.
- **Bridge -** It combines the network of encoders and decoders. It is made up of two 3x3 convolutions and ReLU activation function is applied to the resultant value. The ReLU activation function is given by

$$f(x) = \begin{array}{l} 0, \; x<0 \\ x, \; x\geq 0 \end{array}$$

Concept of ResNet50 Model

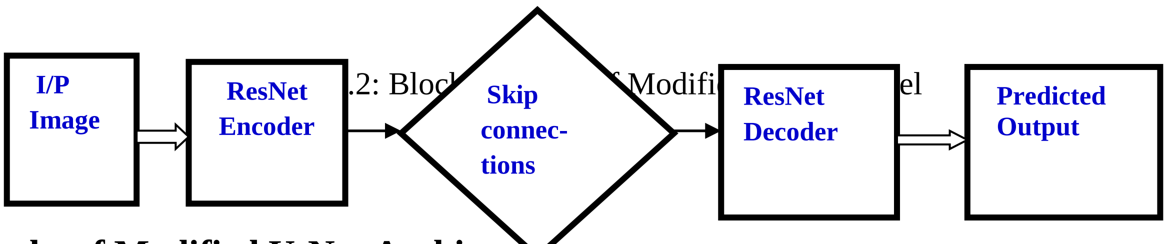
ResNet uses the concept of skip connections which are helpful in solving vanishing gradient problem. The first layer on the ResNet consists of Convolution layer, Batch Normalization layer and maxpooling layer. It has a filter size of 7*7and 64 as its feature map with a stride of 2.The size of the output is given by

$$\boxed{\frac{n+2p-f}{s}+1 * \frac{n+2p-f}{s}+1}$$

Convolution Layer – This layer is used to produce the matrix output for the features taken from the input image.
Batch Normalization – It is a technique used to improve the training of neural networks and stability by normalizing the input to each layer to have zero mean and unit variance.
Max Pooling Layer – It is used to select the corrected feature maps largest element.

Block Diagram of U-Net Architecture using ResNet50 model:

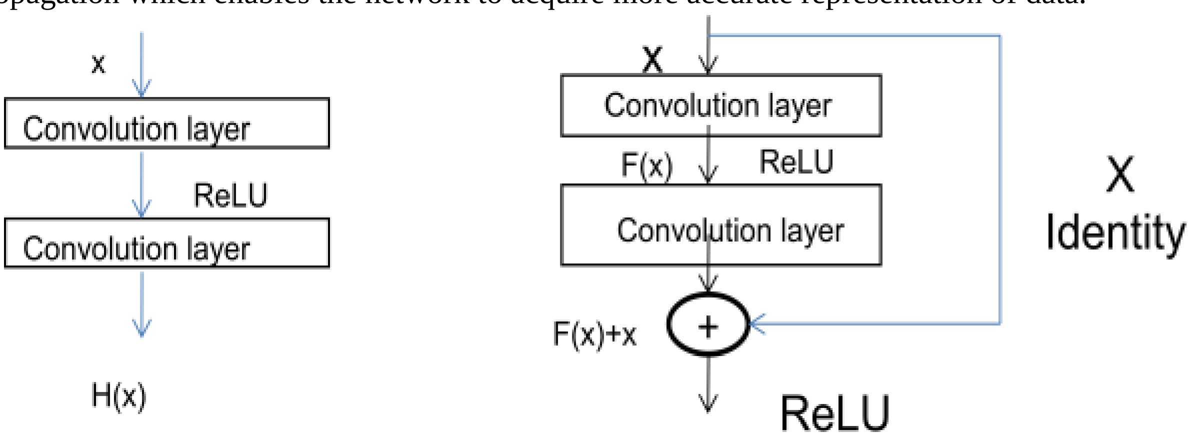
In the modified U-Net architecture, the ResNet model is used for the encoder and decoder blocks. In this the skip connections cross from a portion of same size in the down sampling route to a part in the up Sampling path



Blocks of Modified U-Net Architecture

- **ResNet Encoder** - It has the capacity to deal with complicated visual information and also derive meaningful representations from pictures. It is quite effective in image classification tasks. The feature extraction capabilities of ResNet are used to obtain precise segmentation. It is capable of extracting rich and high level features. As the no. of parameters is reduced in ResNet, the process of segmentation becomes more effective and faster. It is very advantageous in medical analysis as it involves huge amount of data.
- **ResNet Decoder** - This decoder does the process of upsampling followed by 2x2 convolutional layers and utilizes this to create a thorough segmentation map.
- **Skip Connection** – It is provided for matching the decoder block at the output of ReLU.

These skip connections gives the decoder some extra information which helps in the generation of superior semantic features. In addition to this it also serves as a link which may be used as a bypass to facilitate the indirect passage of gradients to the prior layers without causing any deterioration. These skip connections assist to improve the flow of gradients during back propagation which enables the network to acquire more accurate representation of data.



(a) Plain Layer (b) Residual Layer
Figure 3.3. Residual Block of U-Net model

The strategy that supports the network is the residual mapping in which the network fits to relative mapping used by the layers as they learn the underlying mapping. Consequently, if we use H(x) as the starting mapping, the network equation will be:

$$F(x) = H(x) - x \text{ which gives}$$

$$H(x) = F(x) + x \qquad \text{.....(3.1)}$$

A Residual block is a special type of CNN with skip connections and this network is designed to overcome the vanishing gradient problem. The layer groups have skip connection between them so that the training path can be bypassed when the vanishing gradient problem occurs. If there is a layer that is harmful to the performance of the design, adding this sort of skip connection will allow regularization to go around it and bypass it if it is present in the design. This is one of the many advantages of adding this kind of skip connection. Therefore, as a result of this, it is feasible to train a very deep neural network without meeting the obstacles given by vanishing or exploding gradients.

These blocks are incorporated for residual mapping and are denoted by ‘x’ to implement the residual learning process. The two subsequent layers are used as the fundamental components in ResNet. The formula adapted in the ResNet is

$$H(x) = F(x) + x \qquad \text{.....(3.2)}$$

The feed forward neural network technique employing the shortcut networks are used for detection. Without involving the intermediate layers, these shortcuts created a connection between the two separate layers. By integrating the stacked layer output with the inputs through the identifying mapping process, the shortcut connections prevent the need of adding extra parameters.

One of the main benefits of adding this kind of skip link is that, if any layers are present that are harmful to the design's performance, regularization will go around them. Consequently, it is possible to train an extremely deep neural network without running into any issues with disappearing or bursting gradients.

Vanishing Gradient problem: It is a phenomenon which occurs during the deep neural networks training process where the gradients used for updating the network become extremely small or vanishes as the back propagation is done from the output layers to previous layers.

Evaluation Metrics:

IoU (Intersection over Union)

This is the acronym of "Test IoU". This measure is used in the computer vision field to assess the accuracy of segmentation models and object recognition. By dividing the intersection of the two by their union, it calculates the amount of overlap that exists between the ground truth segmentation mask (and bounding box) and the predicted segmentation mask. This yields the overlap measurement between the two masks. The better performance of the model is indicated by a higher IoU score.

$$IoU = \frac{|A \cap B|}{|A \cup B|} \qquad \text{..... (4.1)}$$

Dice Coefficient

By computing the ratio of overlap between the two masks to the total number of pixels in the two masks, the test Dice Coefficient compares the predicted segmentation mask to the ground truth mask. This shows the similarity between the two masks. The score runs from 0 to 1, with 0 denoting no overlap and 1 denoting a perfect match between the anticipated masks and the ground reality. Dice coefficient is a method that is frequently used in medical image segmentation to find the tumor borders in MRI images where the precision factor is most crucial.

$$Dice\,Coefficient = \frac{2|A \cap B|}{|A| + |B|} \qquad \text{….. (4.2)}$$

The test Dice coefficient and test IoU parameters are displayed in the following table. Test IoU of 0.902 and test dice coefficient of 0.948 are found in this suggested model. The comparative study of the proposed model, which is displayed in the following table, leads one to the conclusion that the current approach is superior to the previous approaches.

Area, Centroid and Standard Deviation of the Tumor

Area - It is obtained by summing up the number of pixels in the segmented region
Centroid – It is the mean position of all the pixels, voxels and other elements within the region.
Standard Deviation – This can be obtained by the standard statistical formula given as

$$\sigma = \sqrt{\frac{\sum (x_i - \mu)^2}{N}}$$

Where N- total pixel count, x_i el value, σ – standard deviation

RESULT ANALYSIS

Loss

It is the discrepancy between the output that was actually obtained and the output that should be projected. This loss has to be comparatively less in order to increase the model's accuracy.

Loss graph :

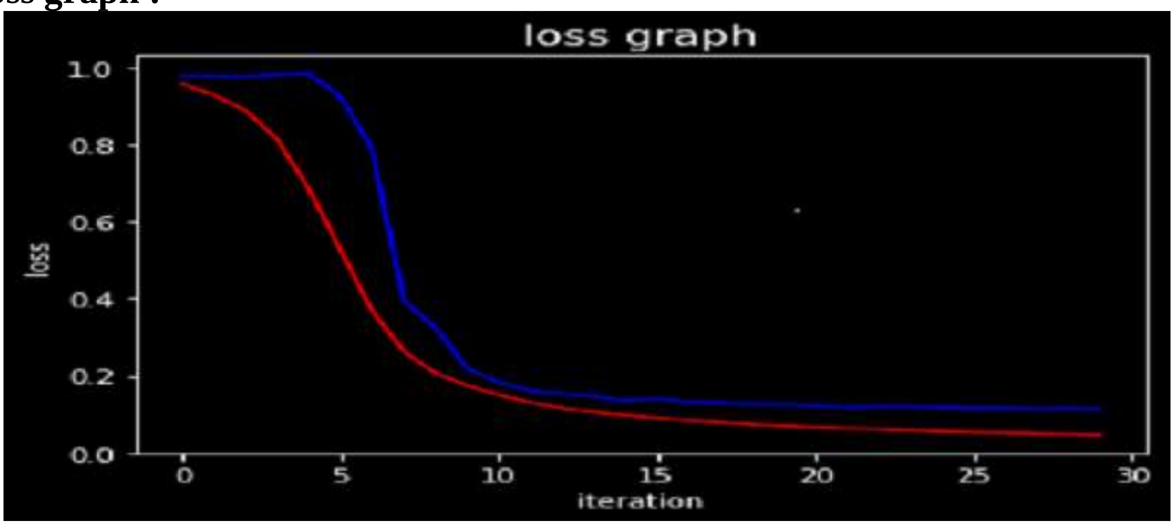


Figure 4.1: Loss graph

Accuracy

It is the measure of how well a model is able to classify the data. It is the ratio of total number of instances that have been successfully classified to the total no. of instances given. The aim of this metric is to obtain highest accuracy proving that the model performs better classification.

Accuracygraph:

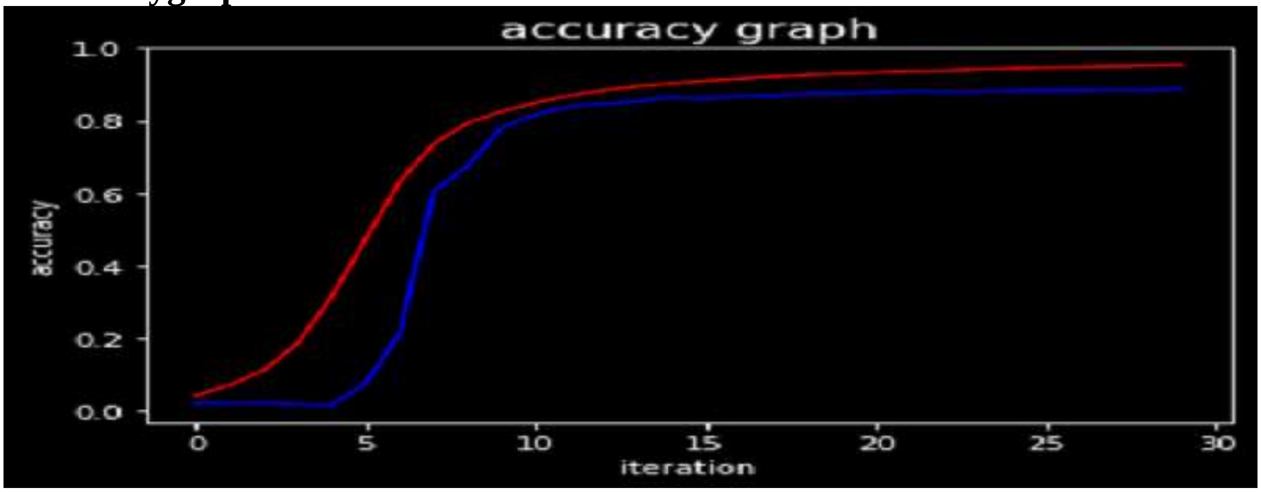


Figure 4.2: Accuracy graph

Table 4.1.: Evaluation parameters of IoU and Dice-coefficient

Metric used	Value
Tested IoU	0.90
Tested Dice coefficient	0.94

Table 4.2: Comparative Analysis with existing methods

Method	IoU method	Dice coefficient method
UNET++	0.82	0.90
UNET	0.79	0.66
Proposed UNET with ResNet	**0.90**	**0.94**

The following figures give the outputs displaying the area of the detected tumor along with the standard deviation and the value of the centroid

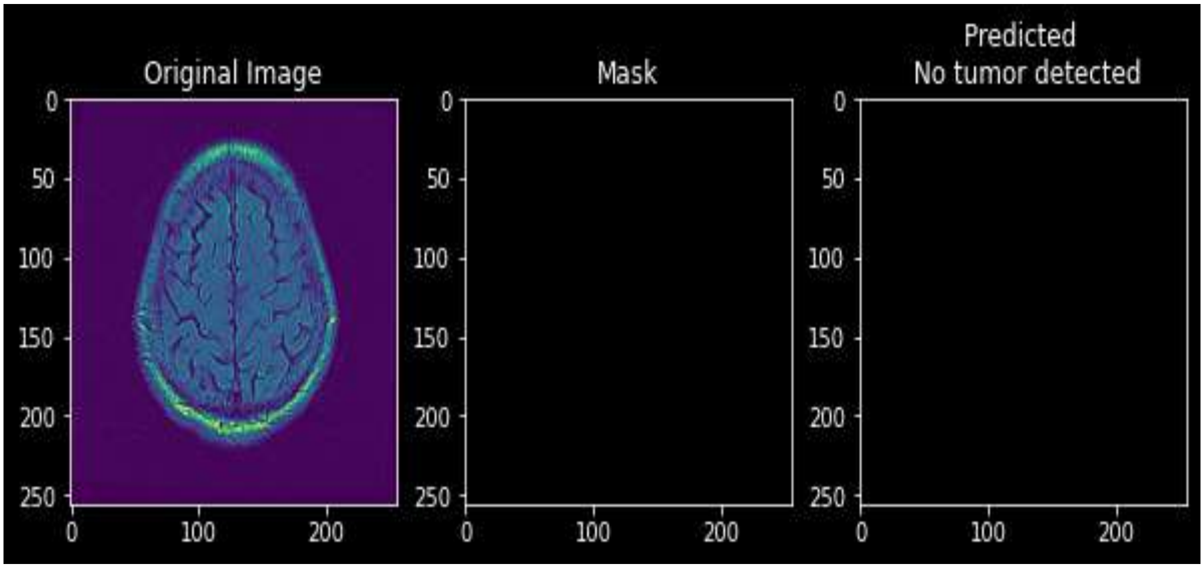


Figure 4.3: Image with no tumor

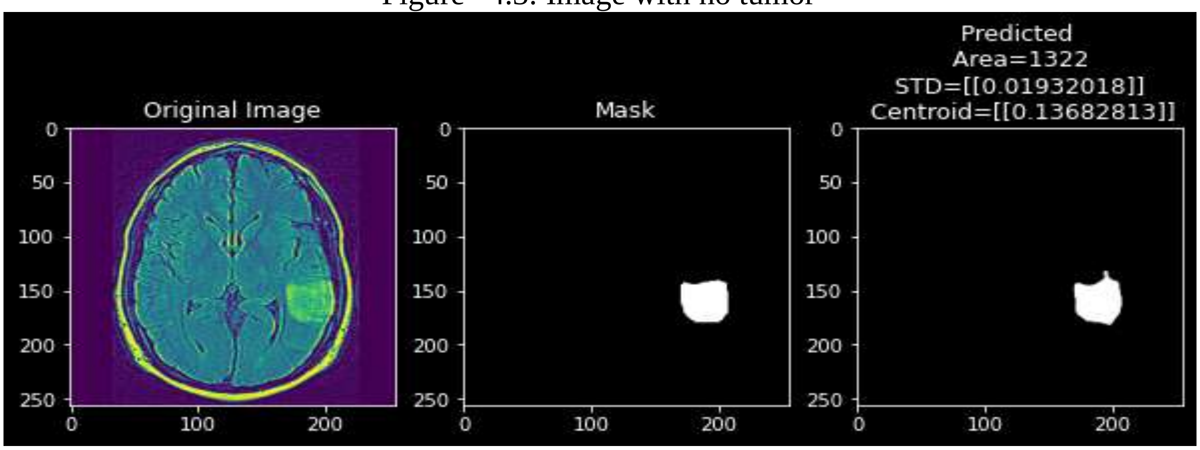


Figure 4.4: Image with tumor of 1322 pixels

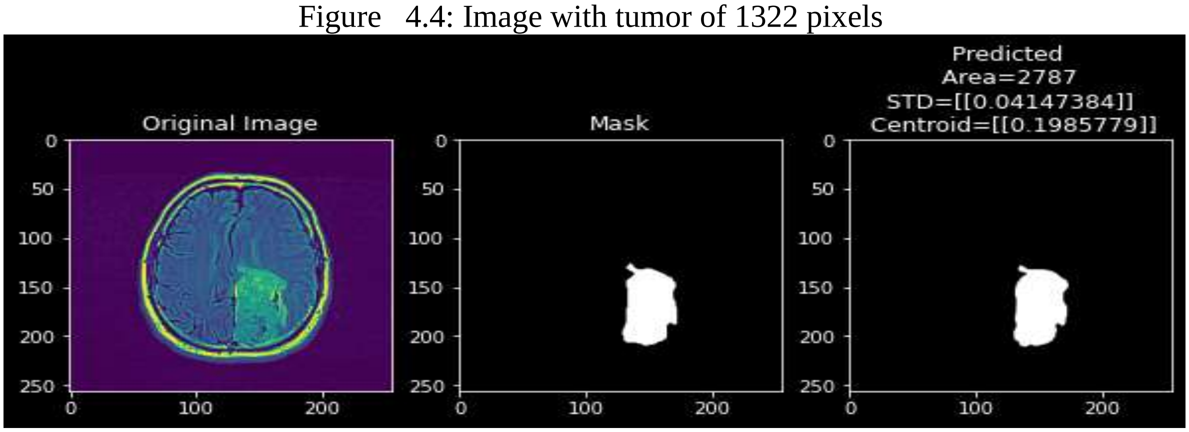


Figure 4.5: Image with tumor of 2787 pixels

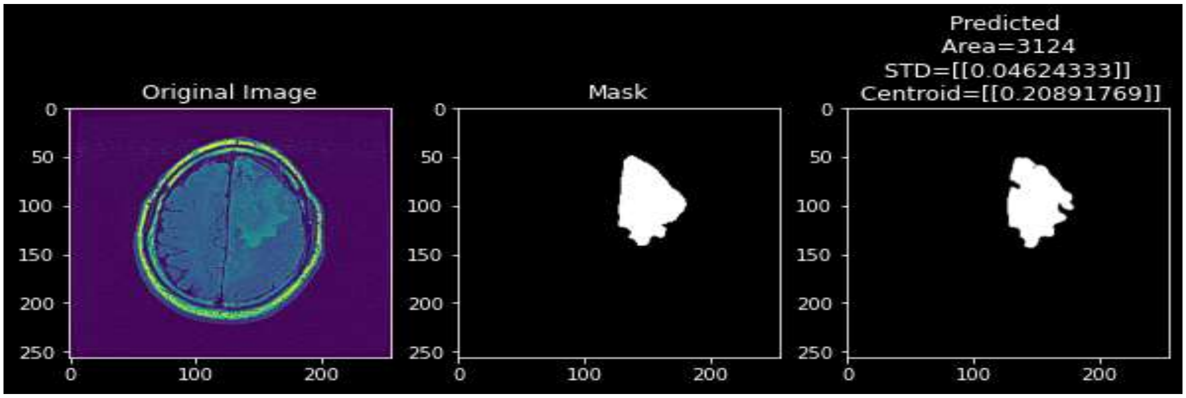


Figure 4.6: Image with tumor of 3124 pixels

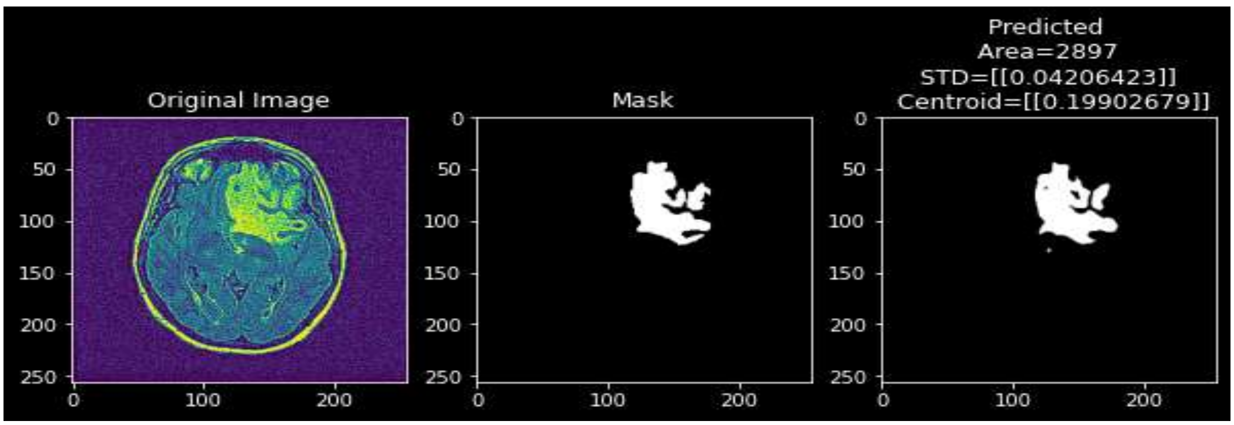


Figure 4.7: Image with tumor of 2897 pixels

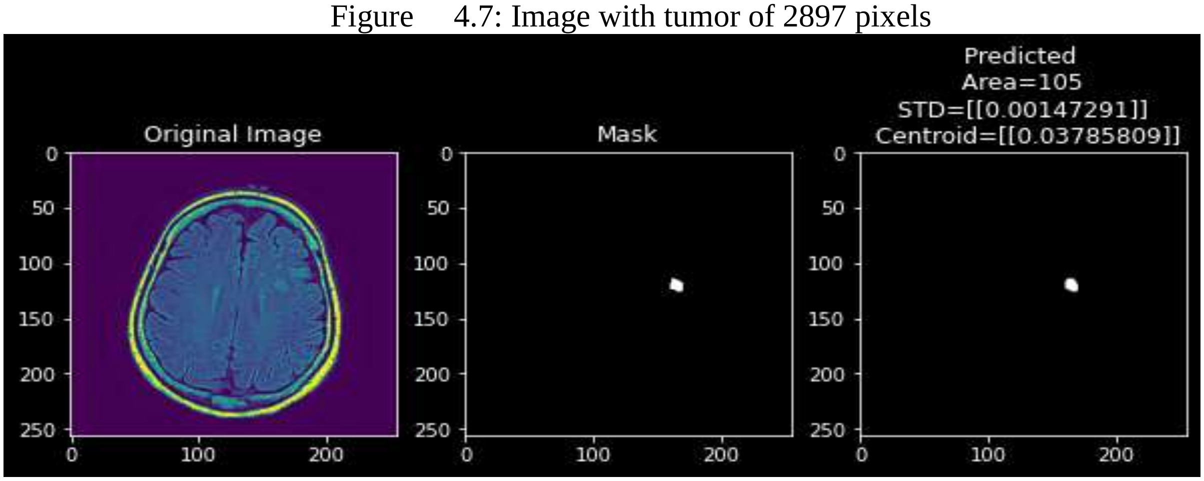


Figure 4.8: Image with tumor of 105 pixels

Conclusion

Although early tumor detection might be challenging, neuro imaging is a crucial component of both the diagnosis and therapy of brain cancers. The resolution of the image being segmented has a significant impact on detection techniques like image segmentation. Magnetic resonance imaging (MRI) tumor segmentation is a new research topic that has emerged in the realm of medical imaging. The brain is as a spongy, delicate mass of tissue. Only consistent conditions allow patterns to emerge and interact with one another. Tumors are masses of tissue that have grown out of control of the usual processes that keep them under control. A tumor is a mass of tissue that will develop into a malignant state. Tumors are formed when cells multiply uncontrollably, leading to the development of cancer. When a U-Net design is considered, cross or skip connections between the network's blocks may be added to help with the forecasts' tendency to be deficient in fine detail. The skip connections cross from a section of the same size in the down sampling route to a part in the up sampling path, as opposed to adding a skip connection every two convolutions as is currently done in a Res Block. More precise and effective segmentation outcomes can be achieved by using ResNet50 as an encoder in U-Net, particularly for medical imaging applications where segmentation is a crucial stage in diagnosis and therapy planning. The Test IoU and Test Dice Coefficient for the proposed model is 0.902 and 0.948, respectively. The big as well as the small tumors can be identified by using this modified U-Net model.

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