LadderNet: Advancing Multiclass Brain Tumor Segmentation using Deep Learning

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***Abstract*—In this research we have performed Multiclass Brain Tumor Segmentation which is a challenging task. In which we have accurately detected the tumor region from the segmentation process. In the paper we have worked on dataset comprised 3064 T1-weighted contrast-enhanced images from 233 patients contains the original images and corresponding Ground truth mask images and our task is to finding the predicted mask from the ground truth mask that detects tumor regions for the different classes in the dataset -U-Net, SegNet, Ladder-Net, V-Net, U-Net with Resnet are the five different segmentation related deep learning models for performing this task. We have compared and found which model is out - performing other models by accurately segmenting the tumor from the segmented predicted mask images by comparing corresponding accuracies, dice coefficients, IOU Scores of all models. LadderNet Model is a newly proposed model in this research, and it outperforms other models by performing with good results and this Model can be considered as the effective Model for the accurate Segmentation of Brain Tumor Disease.**

Keywords—Multiclass Segmentation, Deep Learning, Brain Tumor, Ladder-Net

I. Introduction (*Heading 1*)

The brain is the most vital organ in the human body. Brain tumors are very harmful disease that grow and rapidly spread in the brain and that can cause death. This is the reason why deep learning algorithms are implemented to early detection of tumor disease by segmenting the brain tissues. Brain tumors were generally segmented manually by the medical professionals. This method can be time-consuming in complex circumstances. [2] Automatic and accurate segmentation is essential in the medical field. Image segmenting task is quite challenging part and in the medical image segmentation process it is more challenging and we face many issues in this process of accurate detection of disease from the image segmentation process. [8] Our project is also the medical field related to image segmentation task, detection of brain tumor from the MRI scans of various patients. So, early detection and giving treatment for patients is really a great job. This task is done by medical professionals and finding the tumors from the images and giving treatment may take enormous time. To spot the brain tumor manually depends on the experience of the doctor and in this process many challenges because of the noisy images.[31] So developing the accurate models for automatically detecting brain tumor is very important for faster diagnosis. Machine Learning and Deep learning algorithms are in the accurate diagnosis of the disease. [11] In this project we have used five deep learning algorithms with accurate segmentation of the Brain Tumor Segmentation from MRI images and predicting the disease. We have used five Deep learning models like U-Net, V-Net, U-Net with Resnet, SegNet, Ladder-net.[6] We have collected the data from the medial field consisting of the data comprised of 3064 T1-weighted contract enhanced images belonging to 233 patients. The dataset contains images and corresponding labels mask images or the ground truth mask images. the predicted mask images are generated from the ground truth mask images for accurately detecting the brain tumor. We have compared all models by corresponding Accuracies, dice similarity coefficient (DSC) Intersection of Union (IoU)Scores to know which model works best for our dataset to accurately segmentation of the brain tumor disease. Deep learning has the potential to improve computer-aided medical diagnoses, especially for brain tumors. Machine learning and deep learning algorithms are crucial in healthcare, discovering various serious conditions such as brain tumors. [12] Transfer learning and fine-tuning are very popular deep learning algorithms used for brain tumor segmentation. is deployed, robust and reliable machine learning and deep learning models can be optimally obtained according to a study. [15] This will help us for the early detection of Brain tumor Disease and can be diagnosed in an effective way.

II. Related Work

A. Selecting a Template (Heading 2)

This paper explores deep learning methods, particularly this paper focuses on 3D-U-net Architecture. [2] The dataset contains of MRI scans taken from BRATS2020 brain tumor progression collection it consists of 369 training and validation samples and these samples consists of FLAIR, T1,

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T1ce and T2 modalities with the masks in the dataset.3D-Unet model is used in segmentation process and achieved 72.04 as Mean IoU score. After the introduction of ResNet34 as the pretrained model 3D-ResUnet is used then the Mean IoU accuracy becomes 80.23 and Mean Dice Score of 88.55. This paper describes the use of resnet34 as pre trained model to the 3D-Unet the accuracy scores increases and this paper suggests that to use of efficient Net, inceptionV3 also will increase the scores of evaluation metrics. Alireza Amini et.al [3] The paper mainly focuses on automated segmentation of brain tumors by using the deep learning models like U-Net and U-Net+ Resnet architectures. Paper uses two different datasets and one among is Brain Tumor Segmentation 2018 which includes 285 MRI Scans with four modalities. And the second dataset of BRATS 2015 consists of 274 MRI scans with 220 training and 54 validations images with the same modalities which were used in the last dataset. [16] For the effective Brain tumor segmentation disease works on the 2018 Dataset the mean dice scores are calculated for both U-Net and U-Net++, U-net come with 0.892 and UNET++ comes with 0.903 and for the second dataset BRATS 2015 the scores od Mean Dice scores are U-Net-0.891 and U-Net++ 0. 901.So, the U-Net++ outperforms U-Net model in accurately segmenting brain tumor disease. Alina Elena et.al [4] The Paper used for Segmentation of Brain Tumor Disease by detecting the tumor disease from MRI images. Paper utilizes Brain tumor segmentation 2020 Dataset. The paper focused on three deep learning models like SegNet, Unet3D Resu-net. Dice scores is used to compare all models. In The results ResU-Net achieves 91.4%, U-Net achieves 90.8% AND SegNet achieves 90.4%. ResU-Net outperforms all models. Varun Tiwari et.al [5] This paper uses 2DV-Net model for the accurate segmentation and prediction, [14]and it used Brain Tumor segmentation 2020 dataset it contains four MRI modalities: T1, Y1Gd, T2, FLAIR.V-Net architecture combined with convolutional layers for feature extraction. For the V-Net Model The results calculated on Dice Coefficient, Accuracy. Dice Coefficient scores for training and testing are 97.74 % and 99.67% respectively. Accuracy values for training and testing are 99.71% and 99.63% respectively. Jason Walsh [6] The paper expresses the challenges for brain tumor detection from the MRI images through segmentation. The Dataset contains 3064 brain MRI scans of 233 patients with diseases meningioma, pituitary, and glioma tumors. This dataset contains images with corresponding ground truth masks. This paper used U-Net and SegNet deep learning models for accurately segmenting brain tumor. According to the results of U-net model the Dice Similarity Coefficient Score is 0.76 on the test dataset with precision score of 0.90 And for SegNet Dice (DSC) is 0.67 for test dataset with precision score of 0.90. Therefore, U-Net model outperforms SegNet model in segmenting brain tumor. Zaizuo Tang et.al [7] This paper deals with brain tumor segmentation based on M-UNet model it is the extension of U-Net model network. So, M-UNet is used for the better multiclass feature extraction from the input compared to original U-Net model. The Jaccard Coefficient and Dice Coefficient scores are 0.783 and 0.873 respectively. Therefore, there is improvement of M-UNet Model compared with U-Net original model. M-UNet model introduces multiscale convolutional layers which achieves the better segmentation scores compared original U-Net model. Debdatta Kandar et.al [8] The paper uses three CNN models-U-SegNet, Res-SegNet Seg-UNet for the segmentation of the brain tumor in MRI images. These models are pretrained SegNet, U-Net, Resnet18 for the improvement in accuracy. This paper utilizes BraTs dataset contains four MRI modalities. The results include Global Accuracy, Mean Accuracy, Mean Intersection of Union (MIoU) for the U-Net, U-SegNet, Res-SegNet, Seg-U-Net respectively. The global accuracy for all models is 0.98012,0.98245,0.98854,0.99117 respectively. Mean accuracy of four models is 0.904,0.916,0.933.0.921 respectively Mean IoU of four models are 0.592,0.647,0.689,0.734 respectively.

Ayan Gupta et.al [9] This paper uses the models - U-Net, Attention U-Net, Res-U-Net, Res-U-Net++ and R2UNet with their pretrained architectures. [10] The Dataset contains 3064 brain MRI scans of 233 patients with diseases meningioma, pituitary, and glioma tumors. The results compared with f1 score and mean IoU score. U-Net with VGG pretrained model with scores of f1 and mean IoU are 0.8033 and 0.8322 respectively. U-Net with Resnet152 pretrained model with scores f1 and mean IoU are 0.8116 and 0.8382 respectively. Attention U-Net with Vgg19 pretrained model scores if f1 and mean IoU are 0.8030 and 0.8342 respectively-U-Net scores are 0.8360 and 0.8562 respectively-U-Net++ scores are 0.7969 and 0.8272 respectively. R2Unet scores are 0.8495 and 0.8665 respectively. Recurrent residual U-Net model outperforms all other pretrained models.[10] Jianxin Zhang et.al Paper deals with brain tumor segmentation using deep learning models like U-Net and CNN. Uses the Brain Tumor Segmentation 2019 dataset. Dice scores achieved by the ensemble is 0.846 for the whole tumor. the AGResu-Net a model with residual modules and Attention gates achieves outstanding performance results. It outperforms the all-other models like U-Net, Res-UNet, AGU-Net in terms of dice coefficient. So, AGresu-net will be helpful in accurately Segmenting Brain Tumor. Jamal Riffi et.al [11] The paper proposes the. U-Net Architecture. [30] The dataset used was BraTS 2017 dataset which comprises of both High-grade gliomas (HGG) and Low-grade gliomas (LGG) of the patients records which contains four modalities of multimodal MRI images. The results were calculated on dice score and the overall accuracy of U-Net model, achieves 0.81 DSC score and 90% as overall accuracy for the brain tumor segmentation.[12] Tamanna Siddiqui et.al, This paper mainly focuses on performance of the U-Net model and also U-Net model pretrained models is compared with base U-Net architectures in terms of results like Dice Score, Hausdroff distance. In this paper the dataset used was Brain Tumor 2020 Dataset, U-Net model achieves dice score with 0.905 which is high among all models.[13] Pengyu Li et.al This paper works on effective brain tumor segmentation. Introduced two deep learning models U-Net and U-Net++ for accurate segmentation. Used the Brain tumor 2019 dataset. Results were calculated on dice scores. The Dice scores of U-Net and U-Net++ models, The U-Net++ model outperforms the U-Net model and it is finalized to detect the brain tumor.[14] Guang Yang et.al This paper studies on one of the brain tumor diseases gliomas. V-net deep learning model is used to segment the brain tumor by generating the masks from the input image and finding the predicted mask. V-Net performance is calculated on average dice score, after experimenting the model achieves 0.78 as dice score considered this model has a high scope for accurate segmentation of disease [15] Ping Liu et.al, This paper studies on the brain tumor segmentation from the MRI images the encoder-decoder neural network that is Deep Supervised 3D Squeeze and execution V-Net model. This model is compared with deep supervised U-Net ,3DU-Net, deep Supervised V-

Net and attention - U-Net models. The results are calculated on Dice score. Deep Supervised 3d squeeze and excitation V-Net outperforms other models with high dice score. Concluded as the good method for diagnosis of tumor disease.[16] Seyed Ehsan Roshan et.al, works on the brain tumor disease LGG (Low grade tumor) segmentation. Introduced two U-Net Models and used 2018 brain tumor Dataset for the task. The performances were calculated on IOU, Dice Scores respectively. The results were 0.79,0.88 as IOU and Dice scores respectively. [17] Sunita Roy et.al paper introduced the effective methods for segmenting the different Tumor diseases. Two deep learning CNN models were introduced they are S-NET, SA-NET architectures and considering the U-Net as base model. Results were calculated for both HGG AND LGG based on DSC Score. the S-Net AND SA-Net Model scores for HGG ARE 0.77 and 0.76 respectively. For LGG the dice scores of S-Net and SA-Net were 0.80 ,0.81 respectively. Therefore, considered this model for accurate segmenting the tumor.

III. Proposed Methodology

In this Study we detect Brain Tumors of various types by the segmentation method. We have presented five deep learning models architectures used for the effective Segmentation of the Multiclass brain tumor Disease. The models are U-Net, SegNet, V-Net, U-Net with ResNet, LadderNet. We are compared the models with different results like Accuracy scores, MeanIoU scores, Jaccard Coefficient scores, Dice Score to investigate which model will be works best in the process of detecting the Tumor Disease Accurately and precisely.

A. U-Net

This study proposes the deep learning method, U-net model [2] This Architecture as presented in Fig. 1. features an encoder-decoder structure which contains encoder, bottleneck, and decoder parts in the architecture. Firstly, encoder path work with four convolutional blocks with three convolutional layers each, it followed by the max polling layers which increases the feature maps from 1 to [16]1024 mainly the task of encoder block is extracting the features from the input images, and it reduces the spatial dimension between the layers. Generally, it follows the down sampling approach. And Second part bottleneck part comprises of three convolutional layers with corresponding batch normalization. And the third part decoder path consists of four blocks which use deconvolutional layers to upscale the feature maps to reconstruct the desired segmented image.[4] It increases the spatial dimensions between the layers, this is up sampling process. Finally, the output layer 1 by 1 convolutional layers will map features and will construct the enhanced segmented image.

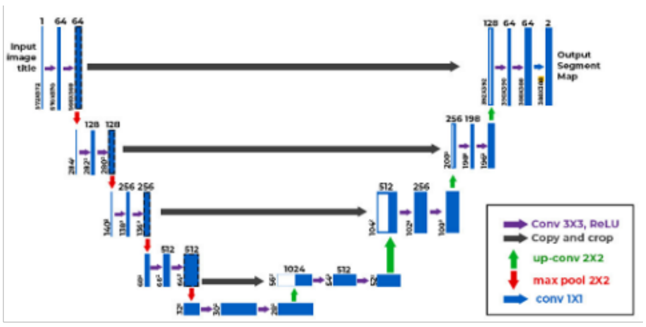

Fig. 1. U-Net Architecture.

B. SegNet

SegNet architecture used for the accurate segmentation of Brain tumor Disease. The Architecture as presented in Fig. 2. consists of Encoder and Decoder blocks.[7] In this encoder path begins with the 3*3 convolutional layers and maxpooling layers involved in the extracting the input images by mapping the partial patterns. And the batch normalization is done and ReLu activation is introduced to understand the complex patterns from the input image and this process continues until it extracts the images. In the encoder path the downsampling process will work because the reducing the spatial dimensions between the layers In the Decoder path will generally do the pixelwise classification and here the up-sampling process takes place by increasing the spatial dimension between the layers. That means upsampled feature is with corresponding feature map from encoder block. [5] In this layer the two 3*3 convolutional layers also follow, and each one followed by the ReLu function, normalization process. Finally in the Output layer the final segmented image is extracted from the encoder-decoder paths.

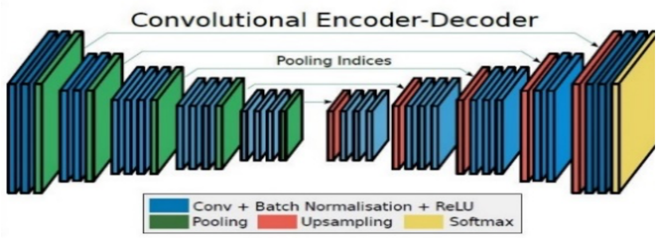

Fig. 2. SegNet Architecture.

C. U-Net with ResNet

This study proposes the deep learning method, U-net model with resnet as the pretrained Model [2] This Architecture as presented in Fig. 3. features an encoder-decoder structure which contains encoder, bottleneck, and decoder parts and the residual networks of the Resnet Model were added to improve the performance of overall Model in the architecture. Firstly, encoder path work with four convolutional blocks with three convolutional layers each, it followed by the max polling layers which increases the feature maps from 1 to [15]1024 mainly the task of encoder block is extracting the features from the input images, and it reduces the spatial dimension between the layers. Generally, it follows the down sampling approach. And Second part bottleneck part comprises of three convolutional layers with corresponding batch normalization. And the third part decoder path consists of four blocks which use deconvolutional layers to upscale the feature maps to reconstruct the desired segmented image.[3] It increases the spatial dimensions between the layers, this is up sampling process. Finally, the output layer 1 by 1 convolutional layers will map features and will construct the enhanced segmented image.

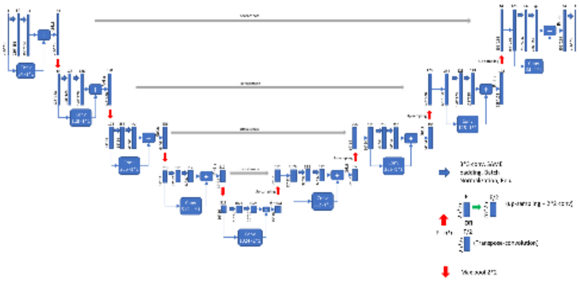

Fig. 3. U-Net with Res-Net

D. V-Net

The V-Net Architecture is Volumetric Network used in the semantic segmentation task. So, this architecture as presented in Fig. 4. will help in the project for accurate segmentation of the tumor. The Architecture comprised of compression and decompression like the encoder the decoder blocks which is done in U-Net, SegNet, U-Net++ networks.[5] In the compression path features will be extracted. The process of down sampling takes place. Features will be compressed through the convolutional layers and each layer implements 5*5*5 filter to capture the features and followed by down sampling takes place with 2*2*2 pooling to reduce the map size, Relu activation function and normalization process will be done. [6]The Decompression layer generally the decoder layer where up sampling process takes place by expanding the compressed features to its original resolution by using deconvolutional layers and here the spatial dimension between the layers increases, the use of Normalization followed by concatenation process will be done by extracting high resolution image, In the final output layer 1*1*1 layer will generate the output segmented image with high resolution and finally this model studied as the accurate method to segment brain tumor.

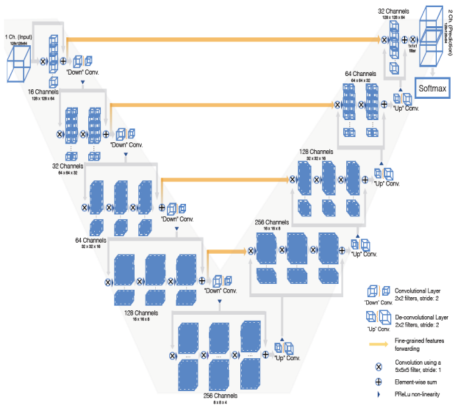

Fig. 4. V-Net

E. Ladder-Net

The LadderNet architecture is generally proposed for semantic segmentation. This model architecture as presented in Fig. 5. generally, combines the benefits of the U-Net architecture and Resnet architecture, so this is reason why this model works well for our project. The architecture will focus on skip connections. The ladder-net architecture comprises of the Encoder and Decoder block and the output layer. In the encoder path the upsampling process takes place with extracting the features. convolutional layers followed by the max polling takes place with ReLu Function used to understand the complex pattern in input images and batch normalization takes place for the stability of the preceding layers. This architecture comprises various residual blocks to its architecture, and it will help in training its deeper layers. Finally Output Layer will segment the High-resolution segmented image.

The LadderNet performance was enhanced by incorporating a refined loss function designed to focus on accurate edge detection, resulting in improved segmentation quality. The training process was optimized through fine-tuning of key parameters and the application of advanced data augmentation techniques, including rotations and elastic transformations, to increase model robustness. Additionally, the use of pretraining on a relevant dataset enhanced feature extraction capabilities. These adjustments, combined with efficient utilization of skip connections, led to superior results compared to the standard LadderNet architecture.

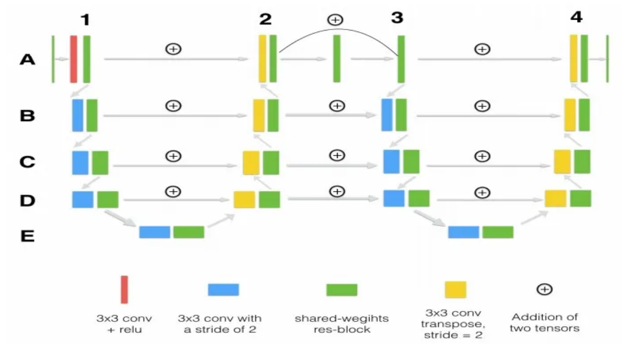

Fig. 5. Ladder-Net

IV. Dataset Description

This project is worked on Brain Tumor Dataset from the Kaggle, which consists of Total 3064 T1-weighted contrast-enhanced images related to 233 patients with [1] Three types of Brain tumor disease like meningioma (708 slices), glioma (1426 slices) and pituitary tumor (930 slices) are there in dataset. Fig. 6. Displays the sample images of different types of tumor images available in the dataset.

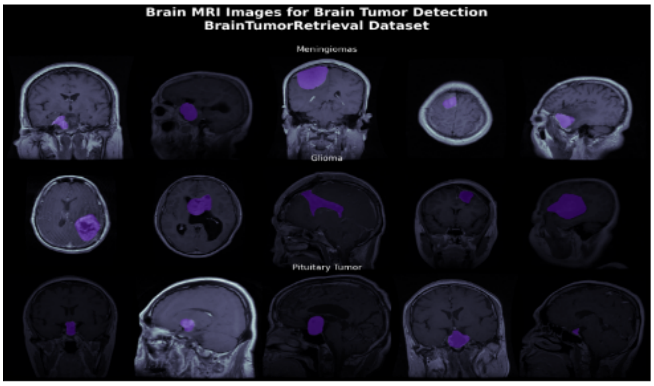

Fig. 6. Brain Tumor types samples from MRI Image Dataset[1].

V. Results

In the Results part the evaluation of the performance for the five Deep Learning Models is done based on four metrics: Dice Score, IoU (Intersection of union) Score, Accuracy and Loss Scores.

TABLE I. Results

Model Name	Dice Score	IOU	Accuracy	Loss
U-Net	73.3	71	98.3	6.2
Seg-Net	74.0	74	98.2	2.6
V-Net	73.5	72	99.6	2.0
U-Net with ResNet	72.0	71.23	98.1	6.7
LadderNet	74.7	75.0	99.5	2.3

Table.1 presents the Results of the five Models calculated on the metrics of Dice Score, Intersection of Union (IoU), Accuracy and loss. V-Net Model achieved the highest accuracy among all the models with accuracy 99.63% and relatively less Dice and IoU Scores. Ladder-Net Model outperforms other models Dice and IoU scores as presented in Fig. 7. 0.7478 and 0.75 respectively and also Ladder-Net model achieves the good accuracy with 99.52%.The SegNet Model achieves good Dice and Iou Scores next to LadderNet model with 74.01 and 74 respectively and accuracy with 98.2%.For the U-Net and U-Net with Resnet models comes with moderate scores among the Models.U-Net Model achieves Dice and IoU Scores of 73.32 and 71 respectively and accuracy of 98.31%.For the U-Net with Resnet model achieves 72 and 71.23 respectively and accuracy with 98.14%.V-Net Model achieves the highest accuracy among the four models and this model lacks performance in Dice and IoU Scores. U-net and U-Net++ Models achieves less scores among the models whereas LadderNet Model has slightly less accuracy and stands as the second highest accuracy model with excellent Dice and IoU Scores compared to V-Net Model as presented in Fig. 8 and Fig. 9. so, the LadderNet Model becomes the effective model for this tumor segmentation task. The ladder-Net was extended to use for brain tumor detection achieves good metrics scores and be considered as the best model for the accurate segmentation of the brain tumor disease.

Visual results for different models (LadderNet, V-Net, U-Net, SegNet, ResU-Net) are presented in Fig. 10, Fig. 11, Fig. 12, Fig. 13and Fig. 14. Results depict the actual mask and predicted mask for the task of multi class brain tumor segmentation.

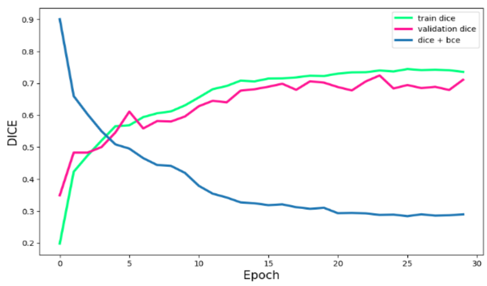

Fig. 7. The plot for dice score and epochs for the LadderNet Model.

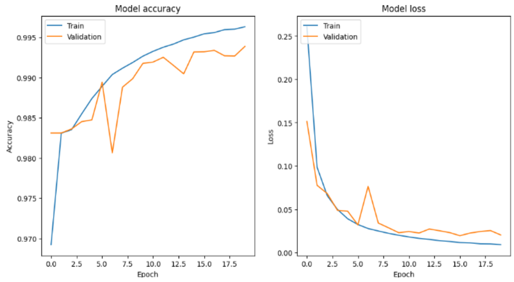

Fig. 8. The plot for Accuracy and loss of V-Net Model.

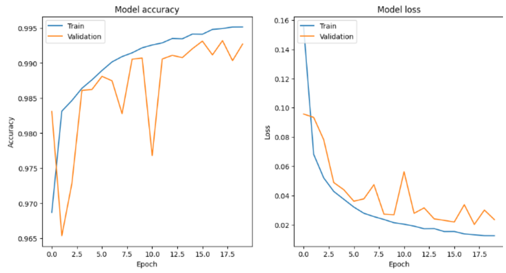

Fig. 9. The plot for Accuracy and loss of LadderNet Model.

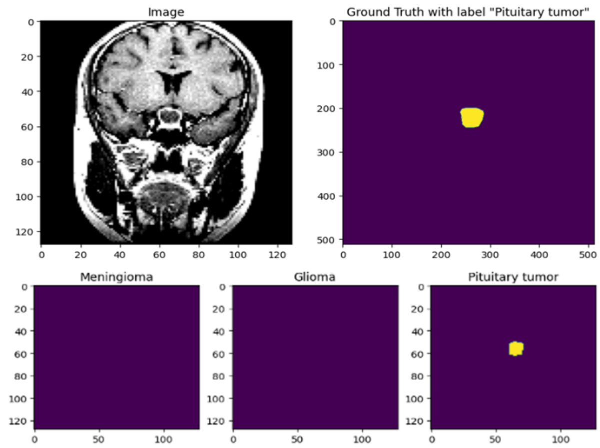

Fig. 10. Pituitary tumor segmentation results achieved for LadderNet Model

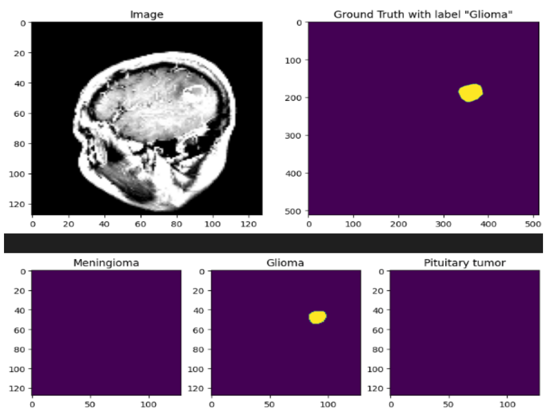

Fig. 11. . Glioma tumor segmentation results achieved for V-Net Model

Fig. 12. Actual and predicted mask for test input image given to the U-Net Model.

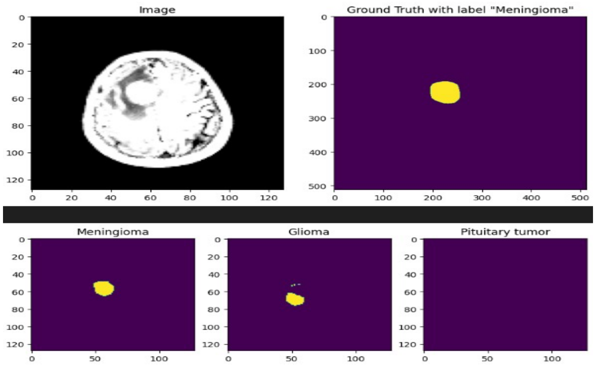

Fig. 13. Meningioma tumor segmentation results achieved for Seg-Net Model.

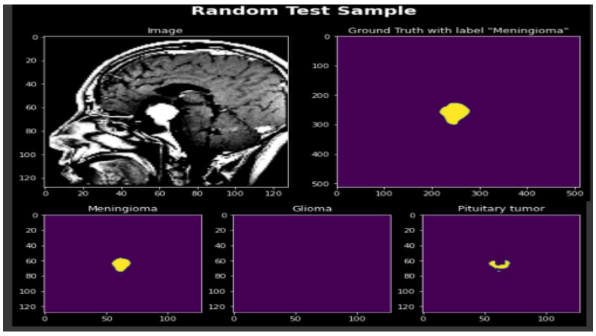

Fig. 14. Meningioma and pituitary tumor segmentation results achieved for Res-UNet Model.

VI. Conclusion

In this research we have successfully developed and evaluated a multiclass brain tumor segmentation with the help of five automated advanced deep Learning Models U-Net, U-Net with Resnet, SegNet, V-Net, LadderNet based on their performance metrics. The V-Net Model achieves the highest accuracy with 99.63% and having the lower Dice and IoU scores with 73.52 and 72 respectively. U-Net and U-Net with Resnet models also reasonably achieves moderate performance among the models, U-Net Model scores a Dice Score of 73.32 and IoU scores of 71 and with a accuracy of 98.31% and U-Net with ResNet model achieves low dice and IoU scores among all the models with scores of 72 and 71.23 respectively and these models is still effective in segmenting the brain tumor but not as accurate as the other three models. The LadderNet model achieves the highest performance among all models with dice and IoU scores of 74.78 and 75 respectively and these models are considered as the accurate model in segmenting and identifying the brain tumor disease from the MRI images. Seg-Net Model also achieves comparatively highest dice and IoU Scores with 74.01 and 74 respectively considered the SegNet model for the accurate segmentation of the brain tumor. Successive Analysis of the Five model Performances is presented to analyze the best model for the accurate segmentation of brain tumor disease is Ladder Net because of its high dice and IoU scores along with a good accuracy. We can consider the SegNet model as the second model with good performance after ladder-Net model. Our study mainly Focused on the model Ladder Net which is proposed for brain tumor segmentation in this work is eventually performing well among all the models. Meningioma, Glioma, Pituitary Tumor Diseases are also predicted and segmented from all models by the input image with corresponding mask images.

Future scope is to expand the training datasets with different brain tumor diseases and stages to increase the model efficiency and finding emerging deep learning models, techniques to further improvement in the segmentation of the multi-Class brain tumor disease with accurate results and developing the software tools, interfaces to accelerate the adoption of our model by the various medical fields.

Conflict of Intrest

On behalf of all authors, the corresponding authors state that there is no conflict of interest.

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