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Brain Tumor Segmentation In Mri Images Using Fully Convolved Neural Network With U Net Model

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Abstract: Extracting The Tumor Affected Area Is A Crucial Task Faced While Diagnosing. As The Mortality Rate Is Higher In Glioma, It Is Necessary To Segment The Region Accurately. Magnetic Resonance Imaging (MRI) Is Opted For Examining The Tumors. Data Produced By MRI Imaging Will Be In High Volume Which Consumes A Lot Of Time For Segmenting Manually. Automatic Segmentation Helps In Earlier Identification Of Affected Areas. Structural Variations In Brain Tumors Bring Difficulties In Automatic Segmentation. In Recent Years, Deep Learning Based Algorithms Are Mostly Preferred For Segmentation. Deep Learning Is Mostly Preferred As It Is Easy To Extract The Features. U Net Based Convolution Neural Network Architecture Is Used Here For The Segmentation Of Brain Tumors. U Net Architecture Has Up Sampling And Down Sampling Which Are Symmetric In Structure. The Number Of Convolution Layers, Pooling Layers And Relu Layers Are Used Based On Our Need. Here 5 Layers Are Used In Which Each Layer Has Two Convolution Layers And A Pooling Layer. The Algorithm Is Tested With The Brats Data Set (Brain Tumor Segmentation Challenge). The Proposed Architecture Achieves The Accuracy Of 96.78%, Sensitivity Of 89.93% And Specificity Of 98.37%. With The Results, We Can Find That The U Net Architecture Helps In Exact Segmentation In MRI Images Compared To All DCNN Algorithms.

Keywords: Brain Tumor, U Net, Fully Convolved Architecture, Deep CNN.

1. INTRODUCTION

Brain Tumor Is One Of The Life-Threatening Diseases And The Mortality Rate Is Quite High. Tumors Can Be Malignant Or Benign Where The Increase In Tumor Cells Leads To Severe Problems. It Is Surveyed That There Is A Very Low Chance For The Genetic Inheritance Of Brain Tumors. Continuous Exposure To Any Chemicals Or Ionizing Radiation Results In A High Chance For Tumors. Treatment For These Diseases Depends On The Tumor Size, Position And Health Condition. Magnetic Resonance Imaging Is Mostly Preferred To Scan The Tumors.

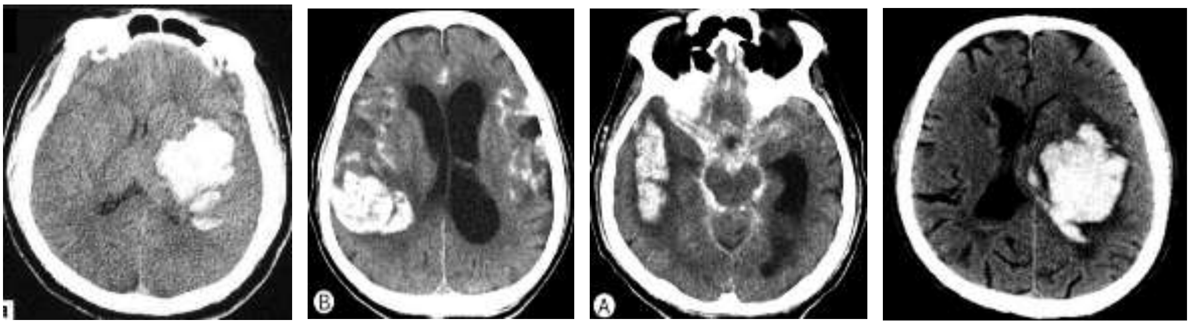


Fig. 1 Data Sets From Brats

The Magnetic And Radio Waves Are Passed To The Affected Area, Based On The Affected Portion Size And The Number Of Images Taken, The Exposure Time Gets Varied. For The Past Decade, Deep Learning Gained More Attention Towards The Researchers In Various Fields Like Pattern Recognition, Image Processing, Speech Processing, And In Automation Industries. CNN Has Been Developed Long Years Back, But It Gained More Attention In Recent Days. Lenet Is First Designed CNN Architecture And It Is Followed By Vggnet, Googlenet, Resnet Architectures. Massive Amounts Of Data Sets Are Available Like Plant Village Database, Brats, Imagenet, DRIVE And STRIVE. Analyzing Medical Images Are More Complicated And Difficult To Obtain Data Sets.

The Paper Describes With The Following Section: "Materials" Explains The Image Datasets Preferred For This Work. "Methods" Includes The Type Of Architecture Used With Its Explanation. "Results And Discussion" Shows The Results Obtained For The Proposed Algorithm And The Results Were Compared With Existing DCNN Architectures. "Conclusion" Provides A Summary Of The Work.

I. RELATED WORKS

Deep Learning Is Widely Accepted By Many Researchers In The Various Fields For Introducing Better Optimization And Suggestion. The Most Dominating Field In Recent Years Is Machine Learning And Artificial Intelligence. Convolutional Neural Network (CNN) Is Mostly Preferred For Object Recognition, Classification, And Semantic Segmentation. Further Improvements In The Architecture Of CNN Outperforms The Existing Models. Multiresunet Architecture Is Discussed In [1] Is The Inspiration Of The Inception Network And U Net. These Modifications Are Done For Improving The Feature Maps. The Analysis Of This Work Is Carried Out With The Public Image Datasets. The Datasets Obtained Are Acquired From Imaging Sources Like MRI, Endoscopy Images, Dermoscopy Images, Electron Microscopy And Fluorescence Microscopy Images. For The Segmentation Of Brain Tumors, Rescuenet Architecture Is Used In The Paper [2]. Brats 2015 And Brats 2017 [1] Datasets Were Used Here For The Experimental Analysis. Unpaired Learning Is Used To Segment The Tumor Regions In MRI Scans. In [3] U Net Architecture Was Preferred For Brain Tumor Segmentation. Various Loss Functions Are Added To Overcome The Imbalance Problem In The Dataset. Semantic Segmentation Of A Brain Tumor Is Done In [4] With The Help Of A Fully Convolutional Neural Network Without Using The Pooling Layer. Deepscan Architecture Was Preferred For This Application Which Results In Exact Semantic Segmentation. Fruit Fly Algorithm And IT2FCM Is Used For Image Segmentation In [5]. The Brain Tumor Is Segmented With The Help Of A Fully Convoluted Neural Network Segnet [6]. Here Efficiency Is Improved By Combing Four Segnet Models That Are Trained Individually. The Feature Maps Generated Will Be Fused Together. Finally, With

The Fused Features, The Classification And Segmentation Will Be Done. The Tool Used Is Found To Be Effective For Diagnosing The Tumors. [8][9][10][11] Suggest Deep Convolution Networks For The Segmentation Of Glioma Tumors. Tumor Segmentation Based On Cascaded U Net And Hybrid Pyramid U Net Was Presented In The Papers [10] And [14] Respectively. For The Segmentation In MRI Images, Unsupervised Algorithms Are Preferred And It Is Proved In [7] That Wavelet Decomposition And Modified Fuzzy Clustering Method Achieves High Efficiency.

II. MATERIALS

The Brain Tumor Segmentation Challenge [7] Brats 2018 Gives The Challenge For The Segmentation Of Brain Tumors. It Provides A Huge Dataset Of Glioblastoma (GBM/HGG) And Lower Grade Glioma (LGG). The Dataset Is Available In The Format: T1 For Native, T1-Weighted For Post-Contrast, T2 Weighted, T2 FLAIR. These Were Captured Under Various Protocols And Strategies. For Structural Modalities Are Present In The Training Datasets Along With The Ground Truth Segmentation Labels[15]. As Discussed In [12] The Tumor Datasets Can Be Categorized Into A) Complete Tumor Region B) Core Tumor Region C) Enhancing Tumor Regions. For Every Category, Sensitivity And Specificity Values Are Calculated With The Proposed Algorithm. Imagenet Is Also Preferred For Getting The Datasets Which Have Large Data Sets With All The Classes

III. PROPOSED METHOD

U NET ARCHITECTURE: U Net Based Fully Convolved Architecture Is Proposed For The Segmentation Of Brain Tumors Which Is Inspired By Sematic Segmentation [19] With Slight Changes[16]. The Proposed U Net Architecture Consists Of Two Paths Which Are Contracting Path And Extracting Path Otherwise Can Be Called Encoder And Decoder[17]. The Complete Architecture Of U Net Is Shown In Figure 2. Contracting Path (Encoders) Is Used For Extracting The Context In The Input Image That Is For Getting The Higher Level Features[18]. The Extracting Or Decoding Path Is The Same As The Other Which Extracts The Precise Localization Information.

2.1 Preprocessing –

The Intensity Levels In The Dataset Are Considered To Be Important For MRI Segmentation To Remove The Artifacts. The Dataset May Be Obtained From Different Sources Also It Should Work With A Single Algorithm[19]. So It Is Necessary To Normalize The Image And Bring The Intensity Level Of The Image To A Standard Size. Batch Normalization Is Mostly Used For Preprocessing In CNN. Standardizing The Input And The Output Of Each Layer Helps In Reducing The Number Of Epochs In The Training Process.

2.2 Contracting And Extracting Path –

As Shown In Figure 2 The Size Of The Mage In The Contracting Path Gradually Decreases On The Other Hand The Depth Of The Image Increases[20]. The Input Image Chosen Is Of Size 572x572x3 And In The End It Reduces To 28x28x1024. The Contracting Path Extracts The Basic Information Present In The Image But It Fails To Locate Its Position. Thus Extracting Path Is Added For Finding Its Precise Location[21]. Five Stages Are Designed And Each Stage Has Two Convolution Layers And One Max Pooling Layer For Extracting The Features And For Reducing The Dimensions[22][26][27]. It Will Be Followed By An Extracting Path That Takes The Input Of Size 28x28x1024 And Produces The Output Of Size 572x572x3. To Provide Better Localization, At Each Stage Of The Decoding Layer Skip Connections Are Added. The Output Of The Convolution Layer At

Each Stage Is Concatenated With The Decoding Layer As Clearly Shown In Figure 2. Concatenation Is Followed By Two Layers Of The Convolution Operation. It Is Named U Net As The Architecture Looks Symmetric U In Shape.

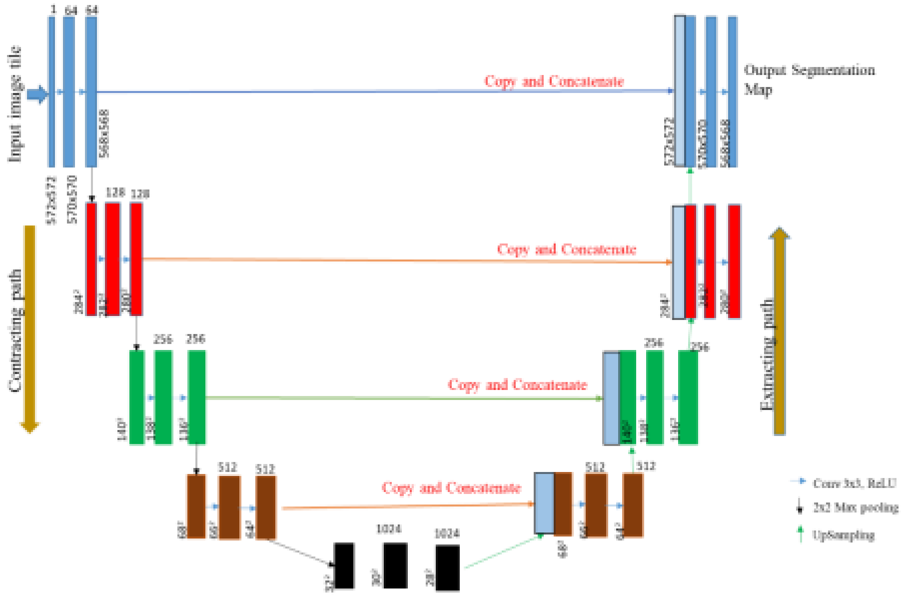


Fig. 2 Architecture Of U Net

2.3 Convolution Layer –

Convolution Layer Is Important In Determining The Feature Maps. More Convolution Layers Are Added For Extracting More Finite Features In The Image[23]. So The Number Of Layers Depends On Our Needs. The Basic Operation Done Here Is Performing A Convolution Between The Input Image And The Filter/Kernel. The Number Of Filter And Its Size Are The Parameters Chosen By Us. The Filter Matrix Will Be Generated Randomly[24]. The Kernel/Filter Is Moved Across The Entire Image And Performs Convolution. The Math Behind This Operation Is Defined As

$$G(m,n) = (I * f)[a,b] = \sum_l \sum_m f(l,m) I[a-j, b-k]$$

I Mentioned In The Equation Is The Input Image And F Is The Filter/Kernel. A And B Are The Number Of Rows And Columns In The Output Matrix. The Stride Of 1 Is Chosen If We Need The Output The Same As The Size Of The Input[25]. Padding Is Done For Recovering The Edge Pixels. Hyper Parameters Are Filter Size, No Of Filters, Stride Size, Padding Size.

2.4 Activation Function –

The Most Preferred Activation Function For CNN Is Relu Which Is Rectified Linear Unit. The Objective Of Using Relu Is To Familiarize With The Non-Linearity In The Output Of CNN. F(X)=Max(0,X) Is The Activation Function Of Relu. The Output Of The Convolution Layer May Be Linear As It Is A Linear Operation. The Network Should Be Trained In Such A Way That It Recognizes The Nonlinear Data. Training Time Take With The Relu Is Much Less Than Compared To Other Activation Functions.

2.5 Training And Implementation –

Training Should Be Done Always With Large Data Sets. The Proposed Algorithm Is Designed In The PC With I7 Core Processor Using MATLAB2018a With 16GB RAM Using Windows 8. The Learning Rate And Maximum Number Of Epochs Are Chosen As 0.0001 And 80 Respectively. The Weights And Bias Values For The Network Are Assigned Based On The Gaussian Distribution.

2.6 Max Pooling Layer –

Pooling Operation Is Performed After Each Convolution Layer. Two Different Types Of Pooling Operations Are Max Pooling And Average Pooling. For Segmentation, Max Pooling Is Mostly Preferred. In Max-Pooling The Maximum Pixel Value In The Group Is Chosen At The Output. The Necessity Of Adding Pooling Layers Is To Reduce The Dimensions Of The Image. The Example Shown Below Has A Pixel Size Of 4x4 And The Output Of The Pooling Layer Is Of Size 2x2. Thus It Helps In Down Sampling The Image.

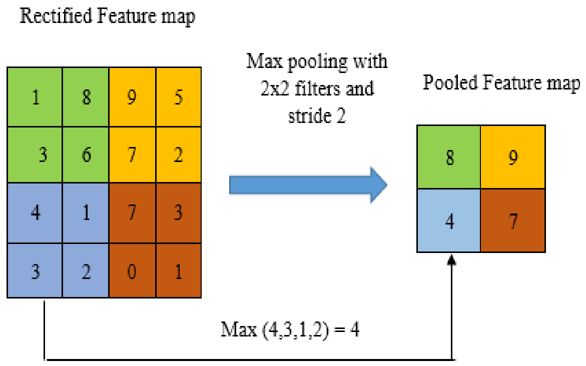
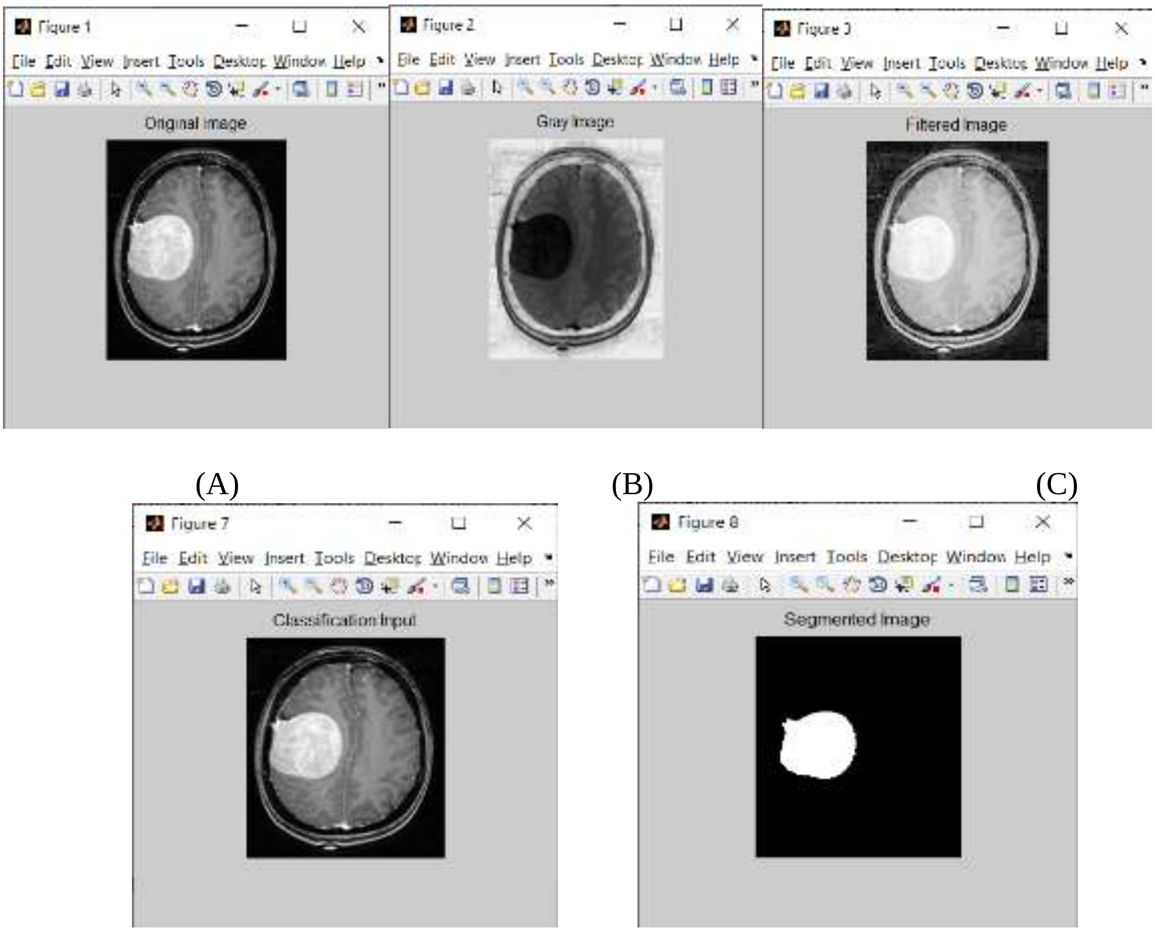


Fig. 3 Max Pooling Operation

2. RESULTS AND DISCUSSION

Figure 4 Shows The Result Obtained Through Various Steps. The Final Segmented Output Is Shown In Figure 4.(E). The Proposed Method Is Tested In Brats 2017 Dataset. It Can Be Classified Into The Complete Tumor, Core Tumor And Enhanced Tumor Region. All The 4 Intratumor Classes Come Under Complete Tumor. The Core Tumor Includes Only The Labels 2 And 3. The Proposed Architecture Is Compared With The Most Existing Architectures Like VGG Net, Fcdensenet, FCNN, DCNN Architectures. Among These Architecture DCNN And FCNN Produced Better Results Compared To Others. Whereas The Proposed U Net Outperforms These Two Architecture. The Algorithm Suits Well For All The Datasets Of Brats. CNN Is Mostly Preferred In Deep Learning Algorithms. Then Came The Pooling Free Networks Which Named As Dilated Convolution. Deep Convolution Networks And Fully Convoluted Networks Have Also Gained Popularity. VGG, Inception Are Designed With Some Modifications In The CNN Architecture. Advantage Of Using CNN Is It Is Flexible And Can Be Modified Based On Our Needs. The Proposed U Net Architecture Is Preferred In Segmentation Which Includes The Contracting Path And Extracting Path. Image Size In Each Layer Is Mentioned In Figure 2.



(A) (B) (C)

(D) (E)

Figure 4.A) Input MRI Image, B) Pre-Processed Grey Scale Image C) Filter Output D) Input To The Architecture E) Segmented Output

Table 1 Below Compares The Proposed Algorithm With The Existing Methods. The Values Shown In Italics Belong To Our Proposed Method.

Table 1: Comparison Of Segmentation Results Of Proposed Architecture With Existing Methods

Publication Year	**Models**	**Sensitivity**			**Specificity**		
		Complete	**Core**	**Enhancing**	**Complete**	**Core**	**Enhancing**
2018	DCNN [13]	0.90	0.89	0.95	0.94	0.93	0.92
2017	VGG[23]	0.9550	0.8186	0.6135	0.9219	0.9200	0.9154
2017	FCNN [22]	0.9589	0.8294	0.6289	0.9244	0.9211	0.9157
2018	Fcdensenet[21]	0.9530	0.8083	0.5975	0.9169	0.9168	0.9135
2020*	***U- Net***	***0.9624***	***0.9368***	***0.6413***	***0.9275***	***0.9260***	***0.9222***

3. CONCLUSION

In This Study, U Net Architecture Is Used For The Segmentation Of Brain Tumor Affected Regions Of The Complete Tumor, Core Tumor And Enhancing Tumor. The Experiment Is Carried Out By First Preprocessing The Input Data. Batch Normalization And Median Filtering Are Done Before Applying The Input Data To The Network For Reducing The Errors And For Adjusting The Intensity Values. Then Data Is Fed Through The Various Layers Of The Architecture Which Includes Up Sampling And Down Sampling. Both Look Alike Where The Up Sampling Path Finds The Tumor Affected Areas And Down Sampling Provides The Localization Information. Our Proposed Architecture Produced Better Efficiency In Terms Of Sensitivity And Specificity And The Values Are Mentioned In Table 1.

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