

## MRI Brain Image Segmentation by Fully Convolutional U-Net

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### Abstract

*When there is rapid growth in the research, and it will lead to use off large amount of data to get accurate results. When you are having large number of data then we require new techniques that will gives better performance in processing. The segmentation of a brain tumour is critical for both treatment and prevention. Various researchers proposed different neural network architectures to get better performance in segmentation of the brain tumour. processing this huge data is challenging and time taking process for computational and analysis. In this paper we are discussing about image segmentation by using fully convolutional network U-Net. In the first stage we are performing some pre-processing on data sets by using adaptive filters. In the next step we are using U-Net architecture to perform segmentation and prediction of MRI brain images. In the next step we are performing Contrast Limited Adaptive Histogram Equalization (CLAHE) to equalize images. CLAHE takes care of over-amplification of the contrast. CLAHE operates on tiles of the image, rather than entire image.*

**Key-words:** Medical Imaging, Deep Learning, MRI, Brain Tumor Segmentation, Contrast Limited Adaptive Histogram Equalization (CLAHE).

### 1. Introduction

From last few years deep convolution networks plays an important role in visual recognition tasks [1]. Conventional neural networks are using from long years [2] but the accuracy is limited due to large data sets and networks. Abnormal cell growth will lead to brain tumors in human brain [3]. The brain tumor is subdivided into high quality sub regions those are tumor core, enhance core whole tumor [4,5]. In this the common brain tumor in adults is gliomas and it is two types of low-grade glioma (LGG) and high-grade glioma (HGG). HGG is more dangers than LGG [6]. To split the brain image in

to required manner by manually is very difficult task. So, we develop a new method that automatically perform segmentation and analysis of brain tumor in all aspects of regions in MRI images.

By using machine learning tumor identification is become more reliable then past [7]. Deep learning algorithms are giving good and appropriate results in medical imaging [8,9] and bioinformatics [10,11,12]. Now a days we are using deep learning in many applications such as soft computing and artificial intelligence. Artificial intelligence is one of the major tasks that affect humans' daily lives. In medical image segmentation point of view the most used method is U-Net, it is the most reliable and gives better performance characteristics when compared to others [13]. Specific multipath convolution neural network proposed to segment brain tumor images proposed by Havaei et al. [14]. Boundary-aware FCN was proposed by Shen et al [15]. At present U-Net architecture is good solution for biomedical image data processing [16]. Here we are using LGG Segmentation data set carries images of 110 patients with lower-grade glioma collection with FLAIR sequence, tumor genomic clusters and patient data is provided in data.csv file which is freely available in Kaggle.

## 2. Methodology

In this method, in the first step we are performing image pre-processing to get perfect data sets. Then we are discussing about U-Net architecture. Then the output image is enhanced with CLAHE technique to get better result. In the first step we are going with image pre-processing here deep learning models are robust to noise it is the major drawback in deep learning models so that we must perform some pre-processing in the image before applying to the network.

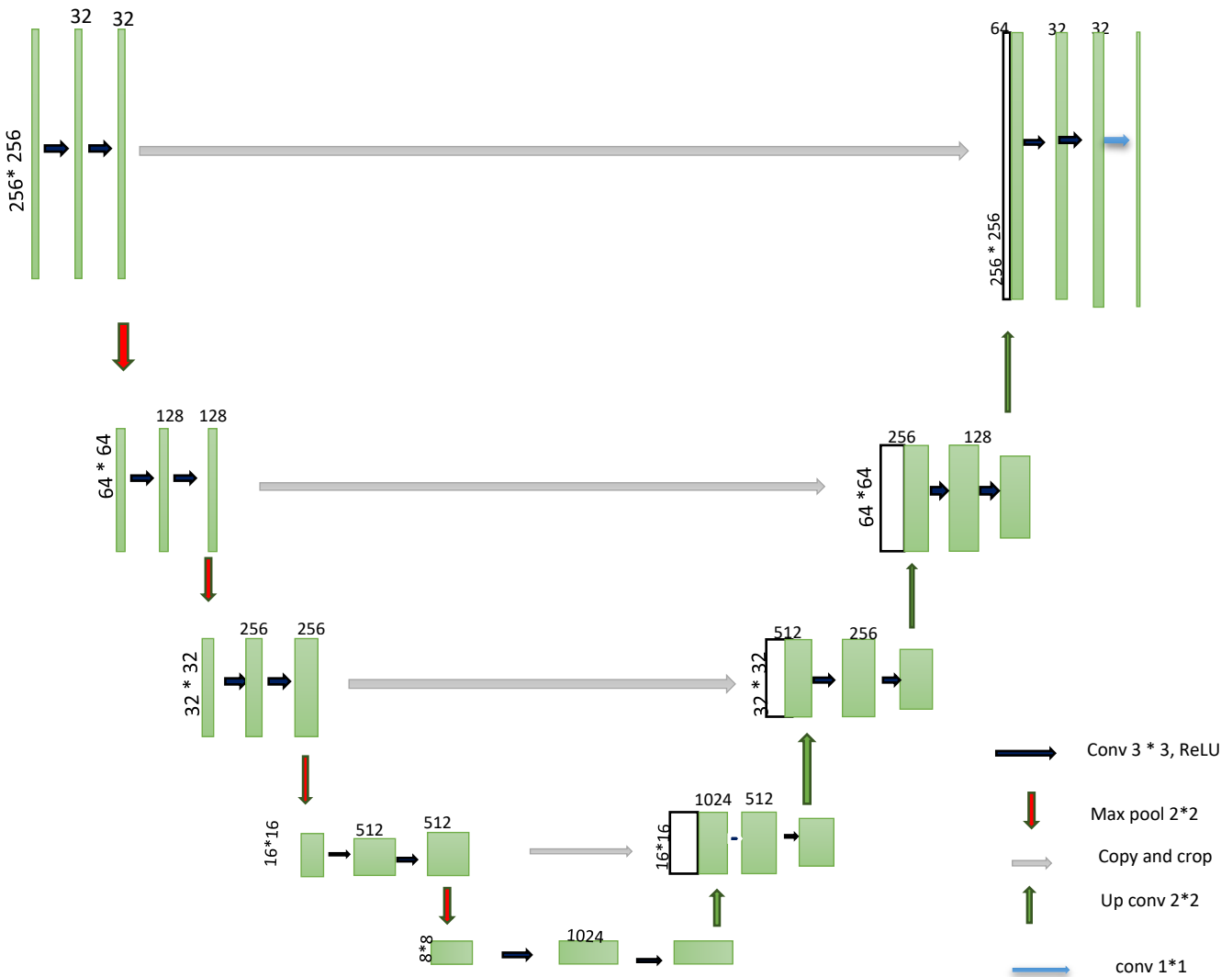
To achieve the contextual information between the shallow and deep layer we introduced this model this can be implementing the bridge between these and cover the gap and enhanced the global features of the network and increasing the efficiency. overall architecture of the U-Net is shown in the figure 1.

In this model, we use the 256 X 256 image resolution as a input and will produce the same output dimensions. As per the image left of the model act as encoder and right act as decoder and conventional layer with padding will allow getting the same result in output that give as input resolution.

In this network encoder and decoder are divided into blocks. Every block on the encoder side consists of the two conventional layers along with the max-pooing layer as well as dropout layer.

Conv2D Transpose is applied at every block of the decoder side to the output of the previous block and dropout applied on top of that for two conventional layers.

Fig. 1 - Architecture of U-Net



Contraction process should happen on the encoder side and expansion process will take care by the decoder. In this model we are using the batch normalization and ReLU activation function except last conventional layer while it uses the sigmoid function and representation as below.

$$ReLU(q) = \begin{cases} 0, & \text{if } q \leq 0 \\ q, & \text{otherwise} \end{cases} \quad (1)$$

$$sigmoid(q) = \frac{1}{1 + exp(-q)} \quad (2)$$

## Building Blocks of Convolutional Neural Networks

**Convolutional layers:** In this layer activations from the previous layer are combined with a small set of parameterized filters, frequently of the size 3 X 3 collected in a tensor  $W^{(i,j)}$  where  $j$  is the filter and  $i$  layer number.

**Activation layer:** The activation function generally defined as the simple rectified linear unit i.e.,  $ReLU(z) = \max(0, z)$ , or variants like leaky ReLUs or parametric ReLUs [17,18] for more info. New tensor will produce when we feed the feature maps through the activation layer.

**Pooling:** When we feed data through one or more convolutional layers then it is in pooling that layer, we called as pooling layer. In this layer, we will provide input small grid regions and we will get only output as single number for each region. we usually define using the max or Avg functions.

**Dropout regularization:** Dropout is a regularization method that approaches training many neural networks with different models in parallel. Dropout is taking an average on the stochastic sampling of neural networks.

**Batch normalization:** The layer which is next to the activation layer typically called as batch normalization layer and standardizes the inputs to a layer for each mini batch which improves the stabilizing the learning process and decreases the epochs to train deep network.

**CLAHE** is a variant of Adaptive histogram equalization (AHE) which take care of the over-amplification of the contrast. Rather than the whole image this CLAHE technique will operate only on the small chunks of the image with high accuracy that is called as Tiles.

### 3. Results

Here we are discussing about tumour detection and segmentation results. We have analysed up to 70 epochs by using U-Net model. In this U-Net model we have achieved training accuracy of 96.97%, validation accuracy of 92.02%, with validation data of 30% and training data 70%.

|                     | pixel accuracy | mean accuracy | mean IU | frequency weighted | geom.accuracy |
|---------------------|----------------|---------------|---------|--------------------|---------------|
| Liu et al. [19]     | 76.7           |               |         |                    |               |
| Tighe et al. [20]   | 75.6           | 41.1          |         |                    |               |
| Farabet et al. [21] | 72.3           | 50.8          |         |                    |               |
| FCN-16s             | 85.2           | 51.7          | 39.5    | 76.1               | 94.3          |
| Proposed            | 92.02          | 53.9          | 42.8    | 77.2               | 96.9          |

Fig. 2 - Loss and Accuracy Curve for 70 Epochs

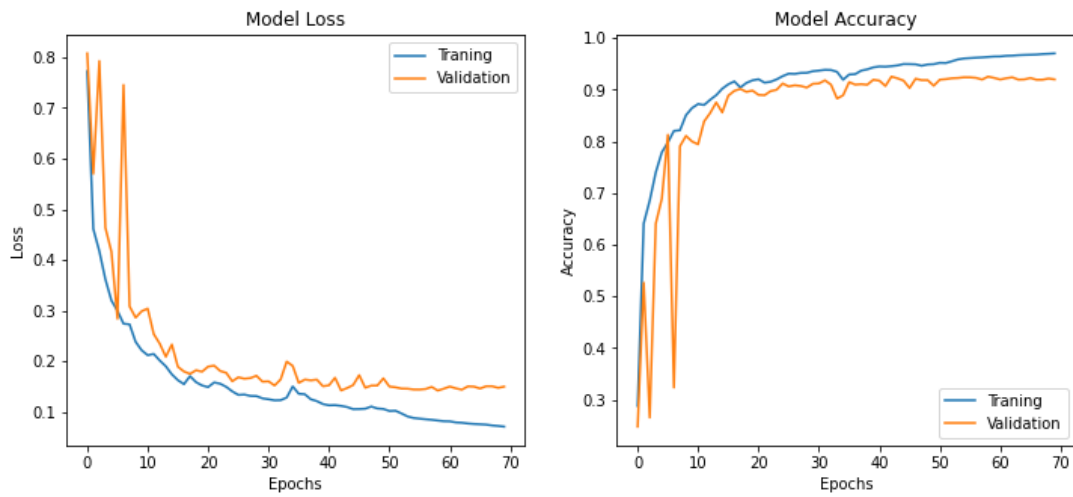


Fig. 3 - Visualization of Prediction for Brain Tumour

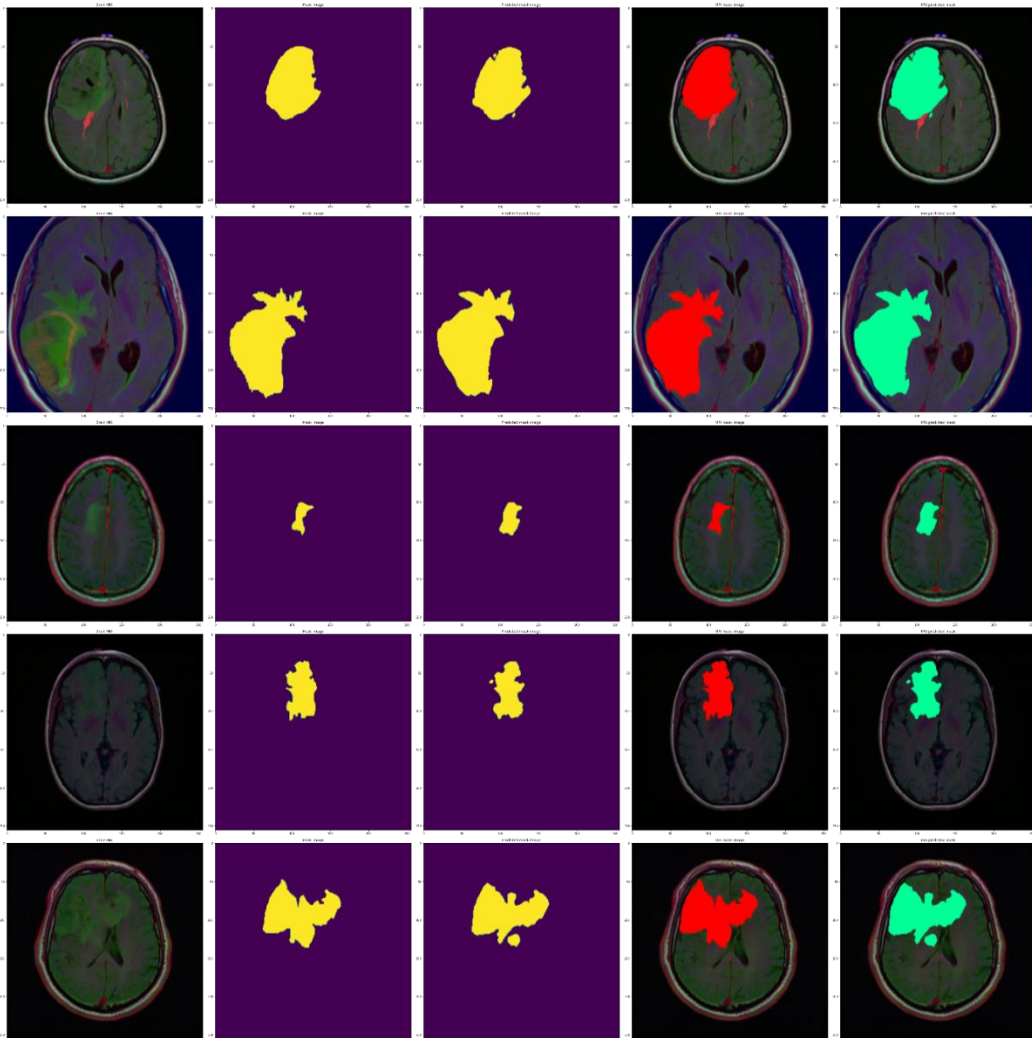
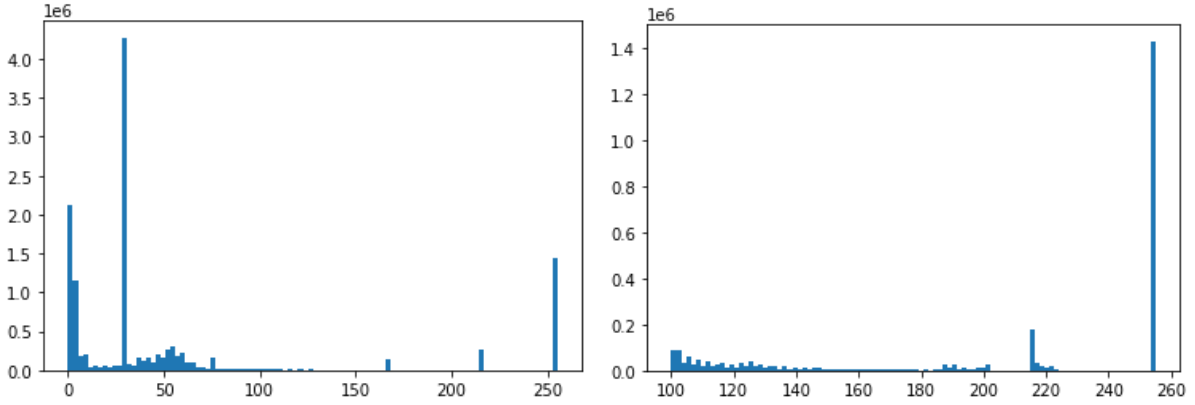


Fig. 4- Histogram Equalization before and after CLAHE



where the quality parameters are

$$\text{pixel accuracy is } \sum_i P_{ii} / \sum_i t_i \quad (2)$$

$$\text{mean accuracy is } (1/P_{cl}) \sum_i P_{ii} / t_i \quad (3)$$

$$\text{mean IU is } (1/P_{cl}) \sum_i P_{ii} / (t_i + \sum_j P_{ji} - P_{ii}) \quad (4)$$

$$\text{frequency weighted is } (\sum_k t_k)^{-1} \sum_i t_i P_{ii} / (t_i + \sum_j P_{ji} - P_{ii}) \quad (5)$$

We present four metrics based on accuracy and region intersection. Let  $P_{ij}$  be the number of total pixels belong to class j from class i,  $P_{cl}$  various classes,  $t_j = \sum_i P_{ij}$  total number of pixels belongs to class i.

#### 4. Conclusion

FCNN is best model for image classification. Here by using U-Net we are improving the quality of classification and segmentation. Due to large number of layers in the network we are getting better accuracy and speeding up the learning process. In this method we are getting training accuracy of 96.9 %, validation accuracy of 92.02%, To increase the accuracy in segmentation process we have to introduce more number of pre-processing and post processing techniques.

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