

# Classification of Brain MRI Images for Cancer Detection using Deep Learning

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**Abstract:** Human system is made up of many organs; of all brain is the first and the leading controller of the human system. Overload cells growing in an uncontrolled manner in brain is called as brain tumor which further leads to brain cancer. MRI (Magnetic Resonance Imaging) is a medical test which uses strong magnets to produce magnetic field and radio waves to generate 2/3 Dimensional image of different body organs and uses computer to analyze the taken image. The brain is composed of 3 types of materials: White Material (WM), Grey Matter (GM) and Cerebral Spinal Fluid (CSF). Through the MRI scan we can view the brain in three different ways: 1]The Axial MRI 2]The Sagittal MRI 3]The Coronal MRI. These images help the Doctor to identify whether that patient is suffering from cancer. The proposed system takes Brain MRI images as an input and pre-processing is performed on it (resizing and renaming). The images will be analyzed using advance imaging technologies. These technologies use Convolution Neural Network and deep learning approach for analysis. After analysis, classifying of whether given MRI images are normal or show a benign or malignant cancer is done automatically, that saves the radiologist's time, increases accuracy and yield of diagnosis.

**Keywords:** MRI Images, U-Net, Ground truth, Tensor flow, Tumor, Brain, Processing, , classification, benign, malignant.

## I. INTRODUCTION

MRI is taken using a scanner which has strong magnets built-in which produces magnetic field and radio waves that scan patient's brain to produce high quality images. MRI uses radio waves to redirect alignment of hydrogen atoms that naturally exist within the body while patient is in the scanner without causing any chemical changes in the tissues. As the hydrogen atoms return to their usual alignment, they emit energy that varies according to the type of body tissue from which they come. The MRI scanner captures this energy and creates a picture of the tissues scanned based on this information. The proposed system takes Brain MRI images as an input and pre-processing is performed on it (resizing and renaming). The images will be analyzed using advance imaging technologies. System will perform the analysis using Deep learning technology on the MRI images and the result will be classification of brain MRI to detect the image depicts brain cancer [benign /malignant /normal]. Our automated system will help the radiologist to analyze the brain MRI images within shorter span of time. Deep learning is a branch of Machine Learning It has Multiple levels of representation and abstraction. It is one step closer to true "Artificial Intelligence" Typically it refers to Artificial Neural Networks . Externally it can be thought of as a black box. It comes Maps inputs to outputs from rules it learns from training. Training comes from known labeled input/output datasets We used keras for Keras is a high-level neural networks API, written in Python and capable of running on top of TensorFlow, CNTK, or Theano. It was developed with a focus on enabling fast experimentation. Being able to go from idea to result with the least possible delay is key to doing good research. Keras is an API designed for human beings, not machines. It puts user experience front and center. Keras follows best practices for reducing cognitive load: it offers consistent & simple APIs, it minimizes the number of user actions required for common use cases, and it provides clear and actionable feedback upon user error

## II. LITERATURE SURVEY

- Detection of Tumor in MRI Images Using Artificial Neural Networks

Automatic defects detection in MR images is very important in many diagnostic and therapeutic applications. This work has introduced one automatic brain tumour detection method to increase the accuracy and yield and decrease the diagnosis time. The goal is classifying the tissues to two classes of normal and abnormal. MR images that have been used here are MR images from normal and abnormal brain tissues. This method uses from neural network to do this classification. The purpose of this project is to classify the brain tissues to normal and abnormal classes automatically, that saves the radiologist time, increases accuracy and yield of diagnosis.

- Survey on Brain Tumor Detection Techniques Using Magnetic Resonance Images

The brain tumor is abnormal growth of cells inside skull which causes damage of the other cells necessary for functioning human brain. The brain tumor detection is challenging task due to complex structure of human brain. MRI images generated from MRI scanners using strong magnetic fields and radio waves to form images of the body which helps for medical diagnosis. This paper gives the overview of the various techniques used to detect the tumor in human brain using MRI images.

- A Neural Network based Method for Brain Abnormality Detection in MR Images Using Gabor Wavelets

Nowadays, automatic defects detection in MR images is very important in many diagnostic and therapeutic applications. This paper introduces a Novel automatic brain tumor detection method that uses T1, T2\_weighted and PD, MR images to determine any abnormality in brain tissues. Here, has been tried to give clear description from brain tissues using Gabor wavelets, energy, entropy, contrast and some other statistic features such as mean, median, variance, correlation, values of maximum and minimum intensity .It is used from a feature selection method to reduce the feature space too. this method uses from neural network to do this classification. The purpose of this project is to classify the brain tissues to normal and abnormal classes automatically, that saves the radiologist time, increases accuracy and yield of diagnosis.

### III. PROPOSED SYSTEM

Image is given input to the application. The patient MRI images are taken and are given to the system or further processing. First stage is of image acquisition. Process of Pre- processing is done. It includes two steps

- Renaming
- Resizing

Image is tested using feature extraction. Image is detected as object. Feature extraction is carried out on detected object.

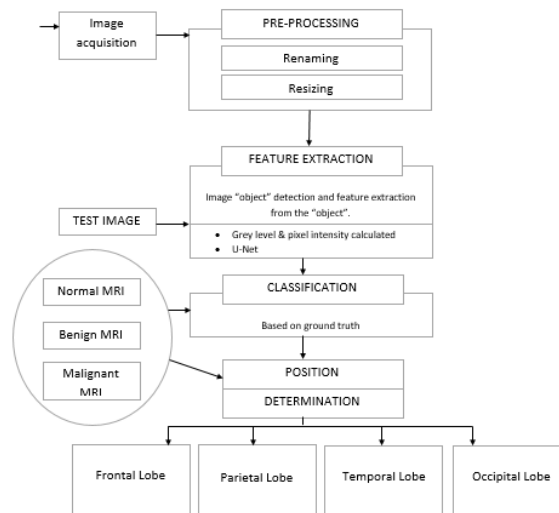


Fig. Architecture structure

U-Net concept is applied for feature extraction. Grey level and pixel intensity is calculated. Based on ground truth , classification process is carried out. Classification i.e. Normal MRI, Benign MRI and Malignant MRI is completed. After classification, position is determined. Four stages are divided i.e. Frontal Lobe, Parietal lobe , temporal lobe and occipital lobe.

### IV. EXPERIMENTAL SETUP

#### A. Dataset

Brain tumor segmentation seeks to separate healthy tissue from tumorous regions such as the advancing tumor, necrotic core and surrounding edema..

We are using BratTS dataset for our experiment

All MRI data was provided by the 2015 MICCAI BraTS Challenge, which consists of approximately 250 high-grade glioma cases and 50 low-grade cases. Professional segmentation is provided as ground truth labels for each case.

The dataset used to train these networks was the BraTS competition. It consists of 210 high grade glioma (HGG) and 75 low grade gliomas (LGG), all of them annotated by experts for all gliomas sub-regions[1, 2, 3, 4]. Only the HGG images were used to train our models. To analyze our results a split was made by patient, such that 70% of the data was the training set and 30% the validation set. A standard U-Net was used to perform segmentation, but instead of 2D images, 3D images were used as input of the network. Appropriate changes were made so that the network would be able to receive these kind of images. T1 and T2 weighted images had their histograms equalized in order to increase intensity contrast. On the other hand, post-contrast T1 and FLAIR images went through standard scaling and normalization before being used as inputs

Here, we are using U-net and ground truth concept. M/L library is used as tensor flow for performing our project. We required Ubuntu operating system. Web Server of amazon is used. We required GPU system as it contains large amount of data. We divide project in 3 modules. The patient MRI images are taken and are given to the system or further processing. After that Pre-processing take place which contain Resizing & Renaming. Next part is of Analysis using Deep Learning. The processed images are analyzed using deep learning technology. At last, Classification and report generation take place. After analyses the images are classified according to the presence of carcinogenic cells. [Normal/Benign/Malignant]

**B. Pre processing**

The first step in pre-processing is image cropping. Some irrelevant parts of the image can be removed and the image region of interest is focused. A gray-scale transformation  $T$  of the original brightness  $p$  from scale  $[p_0, p_k]$  into brightness  $q$  from a new scale  $[q_0, q_k]$  is given by  $q = T(p)$ . If there is a deformation of the expected shape and size of the border and the whole region during the separation of image object from its background, it can be partially overcome. This mask can reshape image objects and provides a separation image objects from each other and from their image background. Edge detectors are collection of local image pre-processing methods used to locate changes in the brightness function. Operators describing edges are expressed by partial derivatives.

**C. U- net and ground truth**

Biomedical images usually contain detailed patterns of the imaged object (e.g., brain tumor), and the edge of the object is variable. To cope with the segmentation for the objects with detailed patterns, Long et al. proposed to use the skip architecture that combined the high-level representation from deep decoding layers with the appearance representation from shallow encoding layers to produce detailed segmentation. This method has demonstrated promising results on natural images and is also applicable to biomedical images. Ronneberger et al. introduced the U-Net, which employed the skip-architecture, to solve the cell tracking problem.

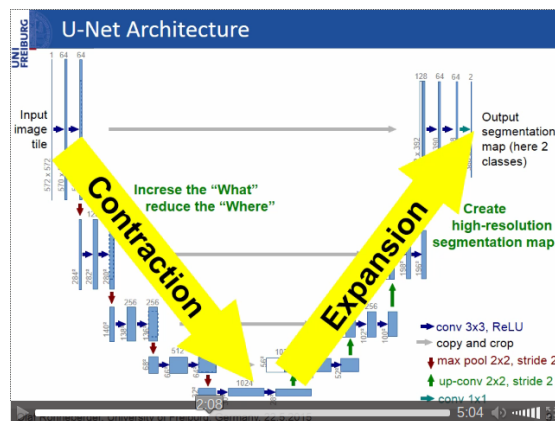


Fig. U- net

The network architecture is illustrated in above Figure It consists of a contracting path (left side) and an expansive path (right side). The contracting path follows the typical architecture of a convolutional network. It consists of the repeated application of two 3x3 convolutions (unpadded convolutions), each followed by a rectified linear unit (ReLU) and a 2x2 max pooling operation with stride 2 for downsampling. At each downsampling step we double the number of feature

channels. Every step in the expansive path consists of an upsampling of the feature map followed by a 2x2 convolution (“up-convolution”) that halves the number of feature channels, a concatenation with the correspondingly cropped feature map from the contracting path, and two 3x3 convolutions, each followed by a ReLU. The cropping is necessary due to the loss of border pixels in every convolution. At the final layer a 1x1 convolution is used to map each 64-component feature vector to the desired number of classes. In total the network has 23 convolutional layers. To allow a seamless tiling of the output segmentation map, it is important to select the input tile size such that all 2x2 max-pooling operations are applied to a layer with an even x- and y-size.

In machine learning, the term "ground truth" refers to the accuracy of the training set's classification for supervised learning techniques. This is used in statistical models to prove or disprove research hypotheses. The term "ground truthing" refers to the process of gathering the proper objective (provable) data for this test. Compare with gold standard. Bayesian spam filtering is a common example of supervised learning. In this system, the algorithm is manually taught the differences between spam and non-spam. This depends on the ground truth of the messages used to train the algorithm – inaccuracies in the ground truth will correlate to inaccuracies in the resulting spam/non-spam verdicts

**D. Tensor flow and keras**

Keras is a high-level neural networks API, written in Python and capable of running on top of TensorFlow, CNTK, or Theano.. Keras is very layer-oriented.

- Use Keras if you need a deep learning library that:
- Allows for easy and fast prototyping (through user friendliness, modularity, and extensibility).
- Supports both convolutional networks and recurrent networks, as well as combinations of the two.
- Runs seamlessly on CPU and GPU.

Keras is a simple, high-level neural networks library, written in Python that works as a wrapper to Tensorflow[1] or Theano[2]. Its easy to learn and use.Using Keras is like working with Logo blocks. It was built so that people can do quicks POC's and experiments before launching into full scale build process. With that in mind its was made to be highly modular and extensible. Now it can be used for a lot more than just experiments. It can help with RNN, CNN and combinations of both. Tensorflow is library for tensor calculation along with neural network. It can write how to deal with tensor to work with neural network model. It is quite flexible to write a new algorithm, but you have to understand why and how algorithms work. Tensorflow is low level implementations of the algorithms and a low level API. On the other hand Keras is concentrated on defining layers for neural network. You don't have to deal with tensors, but quite easy to write, with less code. Since Keras can use Tensorflow for deep learning backend runtime, most outputs are expected to be the same.

Pre-processing : Resizing & Renaming

Training the system: The processed images are analyzed using U- Net.

Prediction: After analyses the images are classified according to the presence of carcinogenic cells. i.e. Normal, Benign, Malignant using ground truth

**IV. RESULT AND EVALULATION**

Input is taken as image. We compare it with ground truth. After applying prediction, we get result as shown in figure 1 and 2.

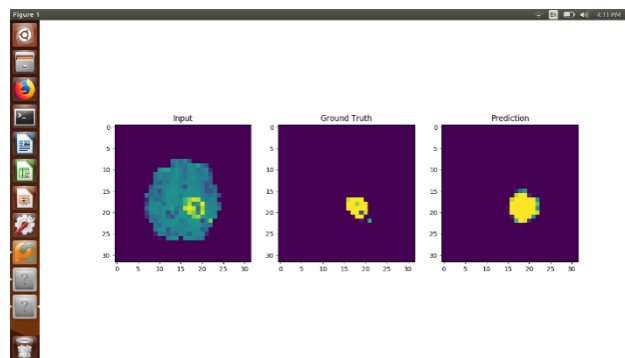


Figure 1

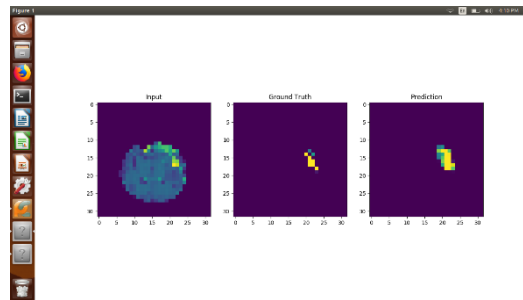


Figure 2

The process of prediction is internally is as shown in figure 3 and 4.

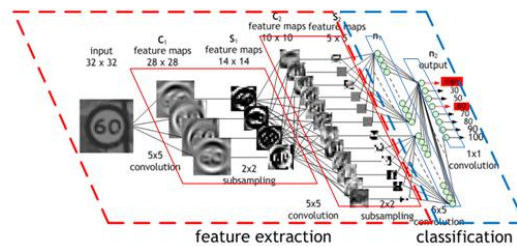
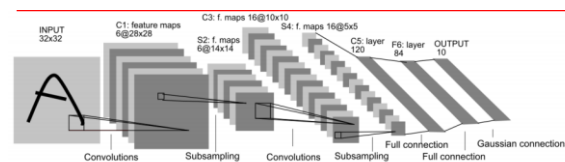


Figure 3



- Input: 32x32 pixel image. Largest character is 20x20 (All important info should be in the center of the receptive field of the highest level feature detectors)
- Cx: Convolutional layer
- Sx: Subsample layer
- Fx: Fully connected layer
- Black and White pixel values are normalized:  
E.g. White = -0.1, Black =1.175 (Mean of pixels = 0, Std of pixels =1)

Figure 4

## V. CONCLUSION

In this proposed work different medical images like, MRI brain cancer images are taken for detecting Tumor. The proposed approach for Brain Tumor Detection based on Convolution Neural Network categorises into Multi-layer Perceptron Neural Network. The proposed approach utilizes a combination of this neural network technique and is composed of several steps including:-Training the system, Pre- Processing , Implementation of the tensor flow, Classification. In future we will take a large database and try to give more accuracy which will work on any type of MRI Brain Tumor.

## VI. FUTURE SCOPE

Results and analysis show that the proposed approach is a valuable diagnosing technique for the doctor to detect the brain tumors. But, in final segmentation, a few other tissues also segmented in addition to tumors. In future work, it would be interesting to include additional feature information. Besides resizing and renaming add more information to the feature extraction in order to make the system more sensitive; information from the textures or location. It will be interesting to continue developing more adaptive models for other types of brain tumors following the same line of work presented here. Characteristic features are more likely to be found in large tumors. Small tumors may not have many of the features of malignancy and may even manifest themselves only by secondary effects such as architectural distortion.



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