ANALYSIS OF BRAIN IMAGES FOR EARLY EXPLORATION OF BRAIN TUMOUR

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Abstract- To increase the survival rate of the brain tumour patients and to have an improved treatment in patients, medical image processing and brain tumour segmentation is an essential support to the diagnosis method. Magnetic Resonance Imaging (MRI) technique is the most popular non- invasive technique. For cancer diagnosis, the brain tumours segmentation can be done manually from MRI, which is considered to be a late identification parameter. To improve the level of accuracy and to have early diagnosis, the proposed project aims in analysing various automatic segmentation methods of brain images to analyse the abnormal image patches. The proposed method focus in employing Convolutional neural networks (CNN) to perform automatic segmentation of patches in brain images. The system takes 2 hidden layers to compute and segment the brain tumour at the earliest by using individual statistical information and population which increases the accuracy and performance rate by minimizing error rate to a negligiblefactor.

***Keywords*:** Image Processing, Filtering Technique Brain Tumour Classification, CNN, Magnetic Resonance Imaging (MRI).

I. INTRODUCTION

Brain tumour is one of the vital organs in the human body, which consists of billions of cells. The abnormal group of cell is formed from the uncontrolled division of cells, which is also called as tumour. Brain tumour are divided into two types such low grade (grade1 and grade2) and high grade (grade3 and grade4) tumour. Low grade brain tumour is called as benign. Similarly, the high grade tumour is also called as malignant. Benign tumour is not cancerous tumour. Brain MRI image is mainly used to detect the tumour. MRI image gives more information about given medical image than the CT or ultrasound image. MRI image provides detailed information about brain structure and anomaly detection in brain tissue. The automatic brain tumour classification is very challenging task in large spatial and structural variability of surrounding region of brain tumour. In this work, automatic brain tumour detection is proposed by using Convolutional Neural Networks (CNN) classification. In the proposed CNN, we will train only last layer in python implementation. We don't want to train all the layers which reduces the computation time. We also investigated the use of intensity normalization as a pre-processing step, which though not common in CNN-based segmentation method. So the performance is high in the proposed automatic brain tumour classificationscheme.

A convolutional neural network is a deep-learning neural network. It has been emulated from the observation of biological process. The architecture of a CNN is designed to take advantage of the 2D structure of an input image (or other 2D input such as a speech signal). This is achieved with local connections and tied weights followed by some form of pooling which results in translation invariant features. Another benefit of CNNs is that they are easier to train and have many fewer parameters than fully connected networks with the same number of hidden units. Convolution neural network is used for automatic brain tumour classification. The brain image dataset is taken from image net. Image net is a one of the pre-trained model. If you want to train from the starting layer, we have to train the entire layer up to ending layer. So time consumption is very high. It will affect the performance. To avoid this kind of problem, pre-trained model based brain dataset is used for classification steps. In the proposed CNN, we will train only last layer in python implementation. We don't want to train all the layers. So computation time is low meanwhile the performance is high in the proposed automatic brain tumour classification scheme. However, as MRI uses magnetic waves, so it is unsuitable for patients with pacemakers and metal implants. Now once we have the scanned image of the brain, it is important to accurately detect the tumour, its size, and its location. All this information is necessary for the Neurosurgeon to complete his diagnosis. This is where Computerized Image Processing comes to help. With the use of different segmentation techniques and feature extraction method, we can accurately detect thetumour.

II. LITERATURESURVEY

Processing an image is a complicated task. Before any image can be processed, it is important to remove any unwanted artifacts it may hold. Only then can the image be processed successfully. Processing a medical image involves two main steps. The first is the pre-processing of the image. This involves performing operations like noise reduction and filtering so that the image is suitable for the next step. The second step is to perform segmentation and morphological operations. These determine the size and the location of the tumour.

A. Image Pre-Processing: Before we begin processing our image it is important that the image doesn't consist of any unwanted data and is in the right format for processing so that the results are accurate. This preparation is classified as pre-processing. Pre-processing involves processes like conversion to greyscale, noise reduction and noise removal,image reconstruction, image enhancement and regarding medical images it may involve steps like skull removal from an MRI.

B. Feature Selection: This becomes even more important when the numbers of features are very large. Feature selection has been the focus of interest for quite some time and much work has been done. With the creation of huge databases and the consequent requirements for good machine learning techniques, new problems arise and novel approaches to feature selection are in demand. Feature selection is the use of specific variables or data points to maximize efficiency in this type of advanced data science. It reduces the complexity of a model and makes it easier to interpret. It improves the accuracy of amodel.

C. Classification: In Classification stage, Convolutional neural networks algorithm is used for classification of brain images. It is a non-parametric method which is used for both classification and regression. The flattened output is fed to a feed-forward neural network and back propagation applied to every iteration of training. Over a series of epochs, the model is able to distinguish between dominating and certain low-level features in images and classify them using the Sigmoid Classificationtechnique.

III. SYSTEM ANALYSIS

A. BlockDiagram

The CNN based brain tumour classification is divided into two phases such as training and testing phases. The number of images is divided into different category by using labels name such as tumour and non- tumour brain image. In the training phase, pre-processing, feature exaction and classification with Loss function. Initially, label the training image set. In the pre- processing image resizing is applied to change size of the image.

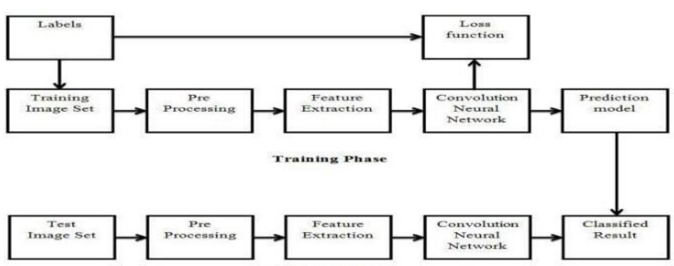


Figure 1:Block diagram of proposed brain-tumour-classification using CNN
(J.Seetha,Brain Tumour classification using CNN,(2018),biomedpharmajournal.org/vol11no3/)

B. SystemArchitecture:

Each input X (image) has a shape of (240,240,3) and is fed into neural network. A Zero Padding layer with a pool size of (2,2). A convolutional layer with 32 filters, with a filter size of (7,7) and a stride equal to 1. A batch normalization layer to normalize pixel values to speed up computation. A rectified linear unit activation layer. Max Pooling layer with f=4 and s=4. A Max Pooling layer with f=4 and s=4, same as before. I've added another pooling layer in order to have less computation cost. A Flatten layer in order to flatten the 3-dimensional matrix into a one-dimensional vector.

A Dense (output unit) fully connected layer with one neuron with a sigmoid activation (since this is a binary classification task)

IV. SYSTEM DESIGN ANDIMPLEMENTATION

Our goal is to propose an automatic brain tumor detection. The automatic brain tumour classification is very challenging task in large spatial and structural variability of surrounding region of brain tumour. For this purpose we choose to employ Convolution Neural Network Algorithm. Following are the steps to be followed to detect brain tumour from MRI image dataset.

A. DataPreparation:

Data preparation (or data pre-processing) in this context means manipulation of data into a form suitable for further analysis and processing. It is a process that involves many different tasks and which cannot be fully automated. Many of the data preparation activities are routine, tedious, and time consuming. It has been estimated that data preparation accounts for 60%-80% of the time spent on a data mining project. Data preparation is essential for successful data mining. Poor quality data typically result in incorrect and unreliable data mining results. Data preparation improves the quality of data and consequently helps improve the quality of data mining results. Our aim is to develop tools to facilitate the tasks of data preparation.

B. DataPre-processing:

For every image, the following pre-processing steps were applied:

1. **Crop the part of the image that contains only the brain** (which is the most important part of the image): you can read more about the cropping technique to find the extreme top, bottom, left and right points of the brain in this blog. Finding extreme points in contours with OpenCV.

2. **Resize the image** to have a shape of (240, 240, 3) = (image width, image height, number of channels): because images in the dataset come in different sizes. So, all images should have the same shape to feed it as an input to the neuralnetwork.

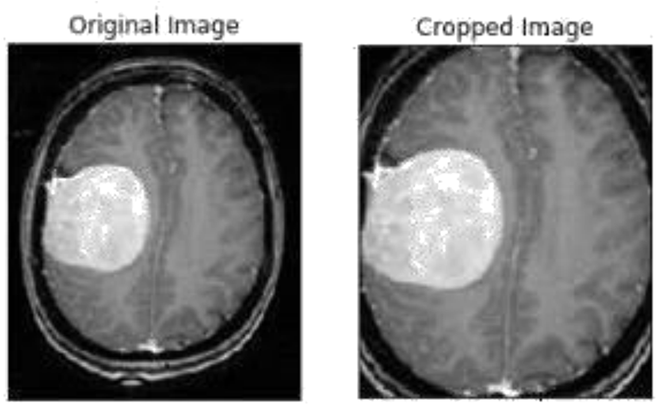


Figure 2: Differentiating the original and cropped images.

3. **Noise Removal:** Erosion erodes away the boundaries of foreground object, Dilation is used to increase the object area and accentuate features.

4. **Apply normalization**: to scale pixel values to the range0–1.

C. DataSplit:

The data was split in the following way:
70% of the data for training**.**
15% of the data for validation (development)**.**
15% of the data for testing**.**

D. DataAugmentation:

Image data augmentation is a technique that can be used to artificially expand the size of a training dataset by creating modified versions of images in the dataset. Training convolution neural network models on more data can result in more skill full models, and the augmentation techniques can create variations of the images that can improve the ability of the fit models to generalize what they have learned to new images. The keras convolution neural network library provides the capability to fit models using image data augmentation via the *Image Data Generator* class.

- Image data augmentation is used to expand the training dataset in order to improve the performance and ability of the model to generalize.
- Image data augmentation is supported in the kerasconvolution library via the Image Data Generatorclass.

E. Image Augmentation with Image DataGenerator:

The keras deep learning library provides the ability to use data augmentation automatically when training a model. This is achieved by using the image data generator We will focus on five main types of data augmentation techniques for image data; specifically:

- Image shifts via the width shift range and height shift rangearguments.
- Image flips via the*horizontal flip and vertical flip*arguments.
- Image rotations via the *rotation range*argument
- Image brightness via the *brightness range*argument.
- Image zoom via the *zoom range*argument.

F. FeatureExtraction:

Feature extraction is a technique which provides meaningful information or characteristics of an image. Feature extraction is the most important task for detection and segmentation of the brain tumour from MR images. Features used for detection and segmentation primarily depend on location, size, shape, and texture of tumour. The extraction of the useful features from MR images is a challenging task as brain images have the complex structures of different soft tissues like GM, WM, and CSF. The texture based features are commonly used for feature extraction, which is further divided in statistical based (1st order and 2nd order texture feature) and transform based texture feature. Also, the alignment based features and edge based features are used for tumour detection and segmentation. The extracted features are then used as an input for any machine learning algorithm for detection or segmentation of the tumour region. The number of features used and also the size of the feature vector determines the capacity of any machine learning algorithm. Sometimes the features computed may contain noisy data and not provide appropriate information needed for segmentation, then it is of no use. So, selection of features and also reduction of the feature vector isneeded.

G. Building theModel:

A Convolution network is able to **successfully capture the Spatial and Temporal dependencies** in brain images through the application of relevant filters. The architecture performs a better fitting to the image dataset due to the reduction in the number of parameters involved and reusability of weights. In other words, the network can be trained to understand the sophistication of the image better. The role of the Convolution network is to reduce the images into a form which is easier to process, without losing features which are critical for getting a good prediction.

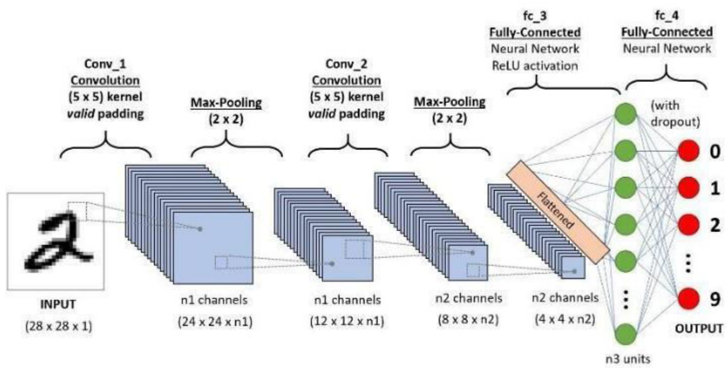


Figure 3:Model outline for CNN sequence
(Sumit Saha,A Comprehensive guide to CNN,(2018),/towardsdatascience.com/)

i ConvolutionLayer:

Our 240x240x1 input image, is carried out the convolution operation in the first part of a Convolutional Layer is called the Kernel, We have selected Kernel size as a 7x7x1 matrix. The Kernel shifts 54,756 times because of Stride Length = 1(Non-Stride),every time performing a matrix multiplication operation between K and the portion P of the image over which the kernel ishovering.

ii PaddingLayer:

Same padding is the concept in which the dimensionality is either increased or remains the same. Here 240 x240 x1 **is** then changed into 242 x242 x1 matrix by applying same padding.

iii PoolingLayer:

Pooling layer is responsible for reducing the spatial size of the Convolved Feature. This is to **decrease the computational power required to process the data** through dimensionality reduction. Furthermore, it is useful for **extracting dominant features** which are rotational and positional invariant, thus maintaining the process of effectively training of the model. Here we are working with max pooling, **Max Pooling** returns the **maximum value** from the portion of the image covered by the Kernel.

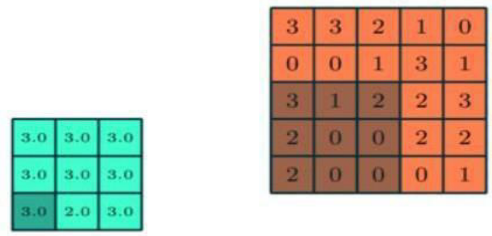
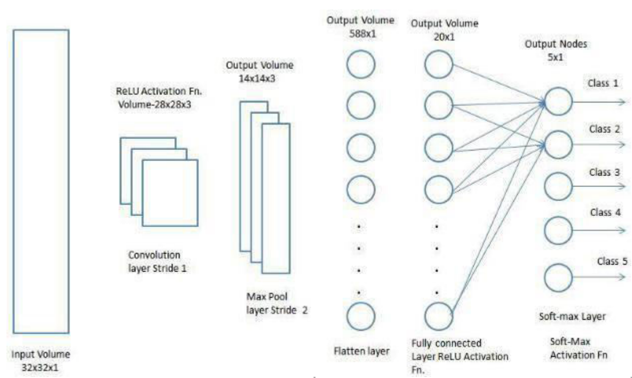


Figure 4: Pooling layer

H. Classification:

In Classification stage, Convolutional neural networks algorithm isused for classification of brain images. It is a non-parametric method which is used for both classification and regression. The flattened output isfed to a feed-forward neural network and back propagation applied to every iteration of training. Over a series of epochs, the model is able to distinguish between dominating and certain low-level features in images and classify them using the Sigmoid Classificationtechnique.



smoothing the convolution filtersubsampling

- The signal transfers from one layer to another layer is controlled by activationlayer
- Fasten the training period by usingrectified linear unit(RELU)

- The neurons in proceeding layer is connected to every neuron in subsequentlayer
- Sigmoid Classification Technique is used as we are predicting tumorous or non-tumorous while testing brainimages
- During training Loss layer is added at the end to give a feedback to neuralnetwork.

V. RESULTS AND CONCLUSION

A. Results:

Our model (the one with the best validation accuracy) detects brain tumour with,

88.7% accuracy on the **test set**.
0.88 f1 score on the **test set.**

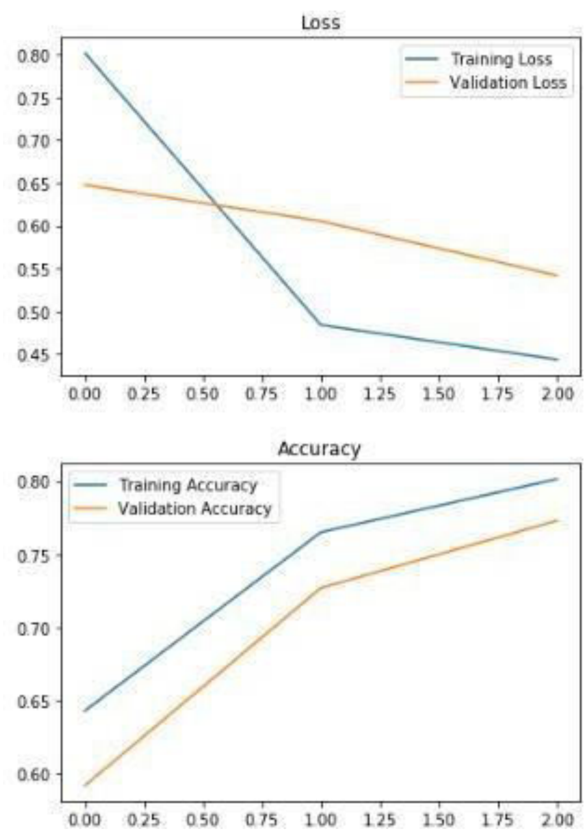


Figure 6: Accuracy results of our model

	Validation Set	Test set
Accuracy	91%	89%
F1 Score	0.91	0.88

Table 1: Performance table of our model:

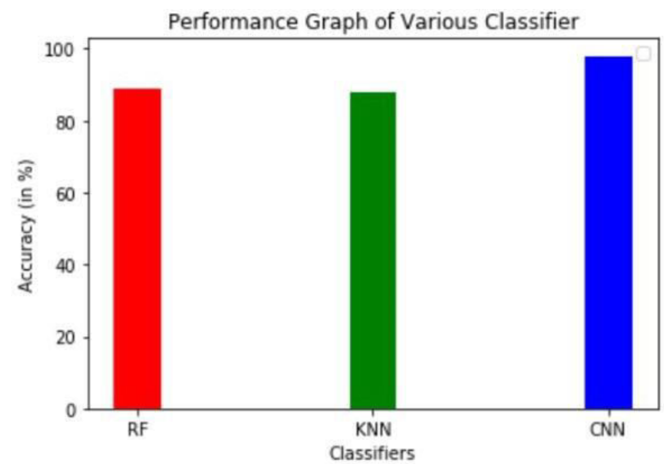


Figure 7:Performance Graph

B. Conclusion:

The main goal of this work is to design efficient automatic brain tumour classification with high accuracy, performance and low complexity. Our Dataset contains tumour and non-tumour MRI images collected from different online resources and efficient automatic brain tumour detection is performed by using convolution neural network. Simulation is performed by using Python Language. The training accuracy, validation accuracy and validation loss are calculated by Gradient decent based loss function to achieve high accuracy. Similarly, the validation accuracy is high and validation loss is very low. Results are analysed and has been proven that Convolutional Neural Network image classification method gives better results compares to other machine leaning classification methods.

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