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A CNN based Approach for the Detection of Brain Tumor Using MRI Scans

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Abstract

In the present day, the rise in the number of diagnosis of brain tumour has reached an enormous height. Gliomas and metastatic brain tumours are found to represent 30% of all brain tumours that are diagnosed in human beings. Now with such an enormous number, it is very important that a computer-aided detection system must be employed to diagnose the brain tumour cases accurately and efficiently. Moreover, Magnetic resonance imaging (MRI) has established itself to be one of the most effective tools for clinical diagnosis and more specifically one of the most desired imaging modalities when it comes to the cohort of the complete neuroimaging ecosystem. The proposed work leverages MRI scans (axial slices) to detect the type of brain tumour. The dataset used in the study contained the data of three most commonly diagnosed brain tumours namely, glioma, meningioma and pituitary tumours. For the classification purpose a 2D Convolutional Neural Network (CNN) was designed which propelled an overall accuracy of 91.3% and a recall of 88%, 81% and 99% for the detection of meningioma, glioma and pituitary tumour respectively.

Keywords; *brain tumor, cnn, imaging, mri, deep learning.*

I. INTRODUCTION

Brain is considered as one of the most important and cumbersome structure of the human body. It is primarily the control center of the central nervous system and is responsible for performing the daily voluntary and involuntary activities in the human body. The tumour is a fibrous mesh of unwanted tissue growth inside our brain that proliferates in an unconstrained way. It perpetrates interruption of the normal function of brain cells and causes lethal issues for the people suffering from it and can lead to death if they are not detected early and accurately. Tumours are primarily classified on two premises: malignant or benign and the place of origin. The benign form can be easily discriminated and have a slow maturation rate and has well-defined borders. Cancerous tumours are known as malignant [1]. These types of tumors are very pugnacious and lethal in nature and are difficult to notice. And also, these type of tumors affects other parts of the brain and also spinal cord [2]. With 14,000 deaths every year, Malignant tumors are known to be the most dangerous tumors [3] For the detection of tumor the doctors or physicians typically leverage Computed Tomography (CT) or Magnetic Resonance Imaging (MRI). MRI is one of the scanning technology that provides high contrast scans and furnishes detailed dynamics about the brain anatomy and the aneurysms in the brain tissues [3]. The radiologist consider MRI scans to be the most effective process of scanning the brain tissues to fetch spatial information about the brain and the specific tumor.

Our model presents the design of the automated scheme that is designed to differentiate between normal and abnormal MRI images and classify

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tumour whether they are meningioma tumour, gliomatumour or pituitary tumour.

The paper is organized as follows. The recent work and development that had been done are described under section

In section III the methods and the methodology that is involved in model development are discussed. In section IV we have described our whole paper. And lastly, the paper is concluded in section VI.

II. LITERATURE SURVEY

Many researchers have discussed the importance of image processing in bio-medical in multiple ways which include the processing of images of X-rays, CT scans and MRI to detect the malformation and irregularities in the human body. It has been medically proven that MRI imaging is less harmful than other imaging techniques used because it prevents the body from the exposure of harmful radiations but before analyzing any image, we need to perform a complicated task of pre- processing the images. Image pre-processing is a gradual process where one step leads to another step. It involves step like noise reduction, image enhancement, image contrasting and when it comes down to medical domain involving detection of brain tumour from an MRI scan, removing the imprints of the skull from the image becomes a prime procedure [4]. The next step that would follow is converting the image into grey scaled image, where the pixels of the image only shows intensity without color but even after this step the noise in the image is still present which needs to be eradicated before further processing. The noise in the image is removed by using filtering techniques.

Filtering: It is a technique used to enhance a picture by highlight some features while eliminating other features that do not promote any information gain in a particular study. It involves steps like noise reduction, smoothing, sharpening and edge reduction. The most frequently used filter is median filter which is used for impulsive noise and speckle noise and this technique has an edge over other techniques because of it'sability to preserve the edges of the image without cropping the signal. In [2] and [3] researchers have used median filter to remove the noise that are by default present in an MRI but in some cases [5][6] Gaussian filters based on the principle of convolution is also used to minimze the noise in the image and blur the image by blurring the edges and reducing the contrast. The advantage of using a Gaussian filter is that it works faster than other filters.

Segmentation: After successful removal of noise from an image, the next process that follows is segmentation in which an image is broken down into pixels. This helps in easy analysis of the image to deduce a meaningful observation from it. After the grouping of pixels, each segment of pixel shares some common features. The paper by Amina et al. [5] uses K-means clustering for segmentation. In this method images is segmented to multiple clusters on basis of the nearest mean. Veer et al. [7] in her research used thresholding for segmentation. In thresholding if the value of intensity of a pixel is significant than some predefined constant then it turns the pixel to black and if the value of intensity of pixel is less than the predefined value then it makes the pixel white. An extension of thresholding i.e. Otsu Binarization is used in the paper by Shil et al. [8] in which a binary image is re-created from a grayscale image by dividing into two classes namely foreground and background. In the research by Rathi et al. [10] she has used fuzzy C-means as the clustering algorithm. In fuzzy C-means, data point is allocated to cluster center on the basis of interspace between the center of cluster and the data point [11].Membership towards particular cluster increases as closeness between data and cluster center increases. The edge of using this algorithm is that it gives accurate result for data set which are overlapped. Another type of segmentation process named watershed segmentation is used by [7] in which different objects in an image is separated. The algorithm which assumes pixels values as a local

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topography (elevation) is watershed algorithm. The algorithm floods basins from the markers, until basins attributed to different markers meet on watershed lines. In most of the cases, we chose markers as local minima of the image, from which basins are flooded.

Post Segmentation: Till segmentation the motto of the process remains same, but the further process diversifies into different kind of classification i.e. classifying the image as a normal or an abnormal MRI and then the succeeding research progressed to detect the size and location of abnormalities in MRI (here, tumour). Then researchers added a fresh step to the existing work by classifying the type of tumour into two types namely Malignant (cancerous tumour) and Benign (noncancerous tumour). Once the segmentation phase is successfully carried out many optimization techniques are applied to improve the result obtained.

The first step towards this field of research is detecting any kind of anomaly in a brain, [8] used SVM classification for classifying the image into two types normal MRI and abnormal MRI. [9] detected the of tumour, skull, gray matter and white matter using morphological operations which compares the pixel value of input and output image to get the size of the required part and using manual segmentation she has calculated the area of the tumour which gives the size of the tumour despite the presence of other components of brain. For classification, [5] used the algorithm of SVM family which includes Linear, Cubic and Gaussian kernel functions. This algorithm follows the principle of drawing a hyper plane

by maximizing the margin between the classes by using support. Three types of kernel functions are used to improve the accuracy of result and using SVM classifier he has identified the affected area as well as training his model to predict the grade of the tumour. [7] extended the further classification of tumour into two types –primary tumour and secondary tumour. Primary tumours are those tumours which originate in brain. They are divided into two subtypes: Malignant and Benign whereas secondary tumours are those tumours which originate in another part of the body and spreads to brain eventually. For classification of primary tumour she used Artificial Neural Network (ANN). ANN is composed of many nodes. Each node takes a single input performs an operation on it and passes it another layer of nodes and at output layer each node has a node value. It basically learns using feedback. The advantage of using ANN over other algorithms is that it can handle more variation than any traditional algorithm.

III. METHODOLOGY

The paper discusses the method for detecting abnormalities in the brain MRI images. To be more specific on the use case, an automated system is being developed that scans through the brain MRI images to identify the tissue growth in the brain that is the tumours. In the study a convolutional neural network architecture is devised which accepts 2D MRI image slices and determines the type of error present. The deep learning model designed is trained with three different types of brain tumours namely, glioma, meningioma and pituitary tumours.

Figure 1 described below, shown the complete procedure for the detection and classification of brain tumour. Moreover, in the following segments, each and every step of the procedure is been duly explained.

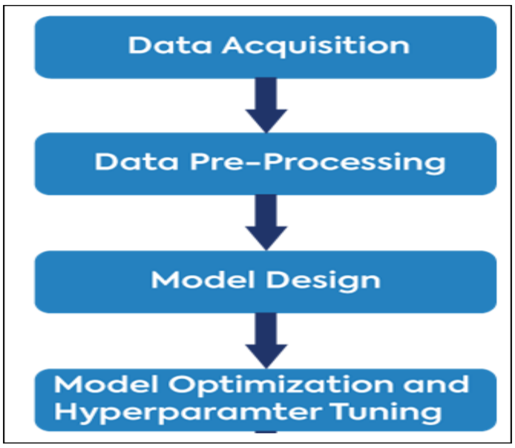

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Figure 1: Flow of control of the complete methodology for the classification of brain tumour.

DATA ACQUISITION

We have obtained the data from [12] for the development of our system. The brain T1-weighed CE-MRI dataset was gathered from Nanfang Hospital, Guangzhou, China, and General Hospital, Tianjing Medical University, China, for the time period of 5 years i.e 2005 to 2010. The set of the data contains 3064 slices from 233 patients, containing 708 meningiomas, 1426 gliomas, and 930 pituitary tumors. The images used have an in-plane resolution of 512×512 with pixel size 0.49×0.49 mm2. The thickness of slice is 6 mm and the gap between slice are 1 mm [13]. Figure 2 represents the data distribution of the 3 different types of tumours. Also figure 3 (a, b and c) plots the 2D scans of the tumours of 3 different types.

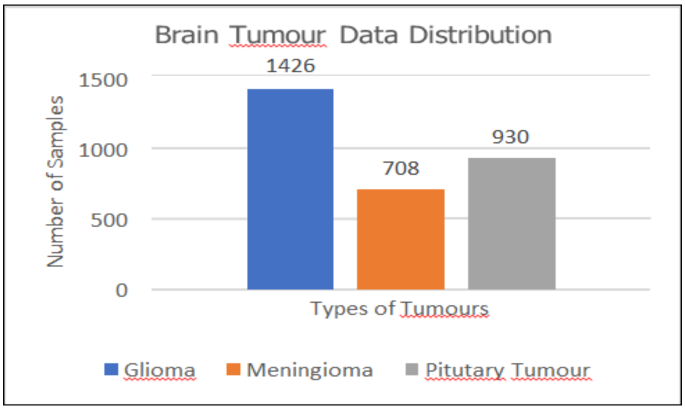
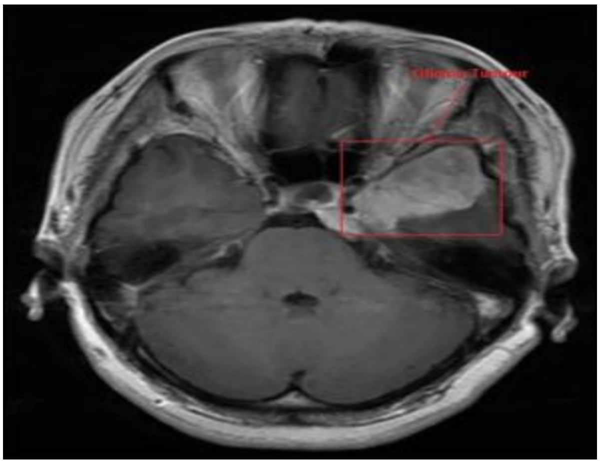
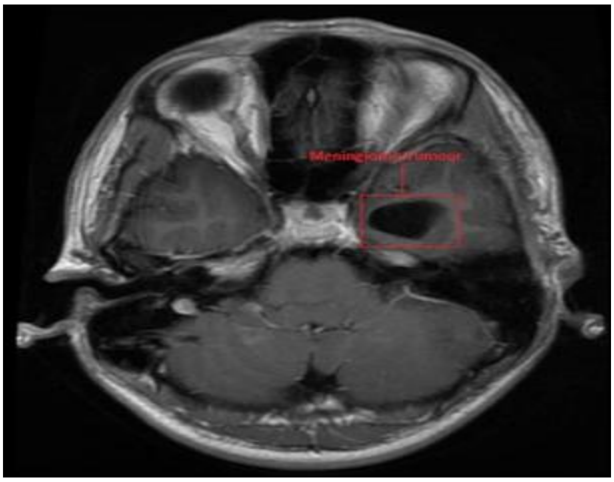


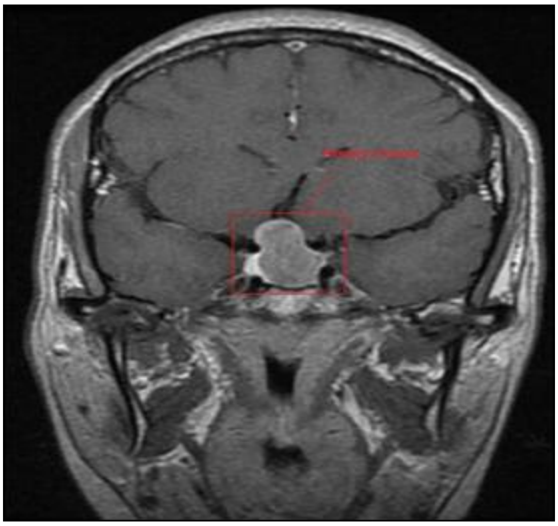
Figure 2: Data distribution of the tumours



(a)



(b)



(c)

Figure 3: (a) Axial Scan of Gliomatumour (b) Axial Scan of Meningioma Tumour (b) Coronal scan of Pituitary tumour

DATA PREPROCESSING

Preprocessing mainly aims at enhancing the quality of MR films and transform it in a form which is suitable for further processing by computer vision system. Moreover, Preprocessing also helps in refining the images and improve some of the parameters such as improving the visual aspect of MR images, improve signal-noise ratio, cropping some of the parts which is not required from the background, making images smoother and retaining the edges [5]. We used adaptive contrast

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enhancement based on altered sigmoid function to improve the parameter of MR image such as signal-to-noise ratio which gave more clarity of raw MR images. Moreover, a Skull stripping activity was also performed. The phenomenon of eliminating the all nonbrain tissues from brain images is known as Skull stripping. We can remove extra cerebral tissues such as skin, fat and skull in the brain images by the help of Skull stripping. Some of the popular technique for skull stripping is skull strippig using image contour, skull stripping based on histogram analysis or a threshold value and skull stripping based on morphological operation and segmentation.

MODEL DESIGN

In recent years it has been seen how supervised learning has created a paradigm shift to solve some most difficult problems. Mostly, after the advent of deep learning technologies it is now a major technology which is used in all the fields namely, healthcare, finance, automated driving etc. [14]. Moreover, the MRI images that are often used by the doctors and physicians for detection of neural disorders needs very accurate and précised examination. However, the examination of such MRI images increases a huge overhead on the physicians and doctors as it needs much expertise. Therefore, leveraging a computer aided detection system for the purpose seems to be very much helpful as it increases the accuracy and efficiency of the diagnosis.

In in the study a deep learning architecture is developed by leveraging 2 dimensional convolutional neural networks for the classification of the type of tumour from MRI slices of the brain. Table 1 shown below, plots the complete model architecture of the developed convolutional neural network model.

Table 1: CNN Model Architecture

Layer	Output Shape	Parameters
Conv_2D	(None, 512, 512, 64)	640
Conv_2D	(None, 510, 510, 64)	36928
Max_Pooling_2D	(None, 255, 255, 64)	0
Dropout	(None, 255, 255, 64)	0
Conv_2D	(None, 255, 255, 32)	18464
Conv_2D	(None, 253, 253, 32)	9248
Max_Pooling_2D	(None, 126, 126, 32)	0
Dropout	(None, 126, 126, 32)	0
Conv_2D	(None, 126, 126,16)	4624
Conv_2D	(None, 124, 124, 16)	2320
Max_Pooling_2D	(None, 62,62,16)	0
Dropout	(None, 62, 62, 16)	0
Flatten	(None, 61504)	0
Dense	(None, 512)	31490560
Dropout	(None, 512)	0
Dense	(None, 3)	1539

The layers used in the development of the convolutional neural network architecture is been defined below.

MODEL OPTIMIZATION AND HYPER-PARAMETER TUNING

The convolutional neural network model that has been developed in the work has used RMSprop optimizer as it gives the best result on this type of dataset. The RMSprop optimizer is alike the gradient descent algorithm with momentum. The RMSprop optimizer limits the oscillations in the upright direction. Therefore, we can increase our learning rate and our algorithm could take substantial steps in the horizontal direction converging quickly. The difference between RMSprop and gradient descent is on how the gradients are calculated. The gradients in RMS prop are calculated on the basis of the running average which is shown in equation 1.

$$(\boldsymbol{w}, \boldsymbol{t}) = \boldsymbol{\gamma v}(\boldsymbol{w}, \boldsymbol{t} - \mathbf{1}) + (\mathbf{1} - \boldsymbol{\gamma})(\boldsymbol{\nabla Q i}(\boldsymbol{w}))\mathbf{2} \quad (1)$$

The parameters of the deep learning model that is weights are being updates using the equation 2.

$$\boldsymbol{w} := \boldsymbol{w} - \frac{\boldsymbol{\eta}}{\sqrt{\boldsymbol{v}(\boldsymbol{w}, \boldsymbol{t})}} \boldsymbol{\nabla Q}(\boldsymbol{w}) \quad (2)$$

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RMSprop Bayesian Sequential Model-Based Optimization (SMBO) has been utilized for knowing the criterion of the optimization algorithm [15]. We generally use Bayesian SMBO to minimze the objective function by developing a probability function which is based on the earlier evaluation outcomes of the objective function.

The set of hyperparameters that we got by using Bayesian SMBO is Learning Rate as 0.001, Rho as 0.9 and decay as 0.1

IV. RESULTS

The 2D convolutional neural network that was developed in the work provided us with quite good and effective results on the predictive power for the different types of tumour. Also, the model developed in the work prompted an average recall and precision of 88% and 91% respectively for all the types of tumours. Moreover the 10-fold cross validation was performed on the complete dataset to check for the generalizability of the model and it was found that the model generalized pretty well and showed a constant tendency towards the precision and recall over the random data folds of training and testing. Figure 4 below shows the confusion matrix of the best obtained model. The few miss predictions that have occurred in the data set are because of the inertial noise that was generated while the patient performed some movement while on the scan machine.

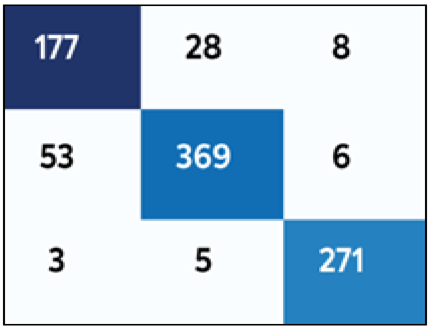

Figure 4: Confusion Matrix

Figure 5.a and b, plotted below shows the Log Loss and the accuracy of the best performing model. It can be seen from the performance graph that the model did not overfit and the validation data maintained a proper generalizability with the trained data.

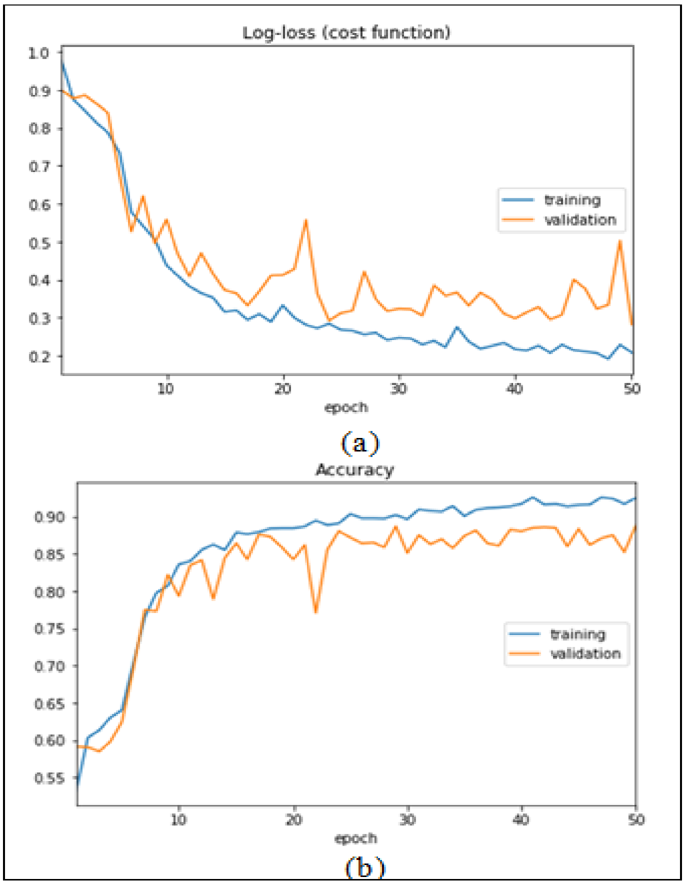

Figure 5 (a) Log Loss plot (b) Accuracy plot.

V. CONCLUSION

The paper discussed and implemented a deep learning architecture by leveraging 2D convolutional neural networks for the classification of the different types of brain tumor from MR image slices. The development of such a system plays a huge role as such systems are very much required for the accurate and efficient diagnosis of such diseases and health problems which are life threatening in nature. The model developed in the study plotted an accuracy of 91.3% and an overall precision and recall of 91% and 88% respectively.

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