Multi-Classification of Brain Tumor Images Using Convolutional Neural Network

HARSH KUMAR CHOURASIA
SRIJAN KUMAR DUBEY
‡Department of Mathematics, Indian Institute of Technology (IIT) Roorkee, Roorkee 247667, India

⋮ **ABSTRACT**

⋮ **INDEX TERMS**

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I. INTRODUCTION

Main Contribution: The major research contributions can be listed as:

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The rest of the paper is organized as follows.

II. STATE OF THE ART

III. DATASET SPECIFICATIONS & PRE-PROCESSING

The dataset used in this paper is collected by Nanfang Hospital and General Hospital,Tianjing Medical University, China from 2005 to 2010 and was made online in 2017. This brain tumor dataset containing 3064 T1-weighted contrast-inhanced images from 233 patients with three kinds of brain tumor: meningioma (708 slices), glioma (1426 slices) and pituitary tumor (930 slices). The data consists of the axial, coronaland, sagittal view of the Brain MRI. Size, shape and location of tumour varies for each MRI image in the dataset. In this dataset tumor size in the range 3x3 pixels to 72x82 pixels with the mean 17x17 pixels and standard deviation 8x8 pixels. So, on average total area of image occupied by tumour is only 1.76 % ($= 17^2/128^2 * 100$). Moreover the tumour can be anywhere present in the image.

It is a common practice for Image Classification using Deep Convolutional Neural Networks to crop, resize and center the subject in the preprocessing stage to increase the effective receptive input region. A new dataset (D2) is created from the given dataset to improve the effective receptive input region by increasing relative proportion of tumour in the input image. A 50x50 image is convoluted through the input
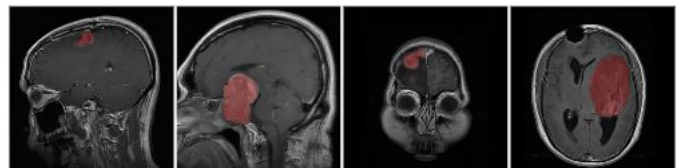

FIGURE 1: The maroon part shows the actual tumor cell. The four above given images show the variation of shape, size and position of the tumor present in the dataset.
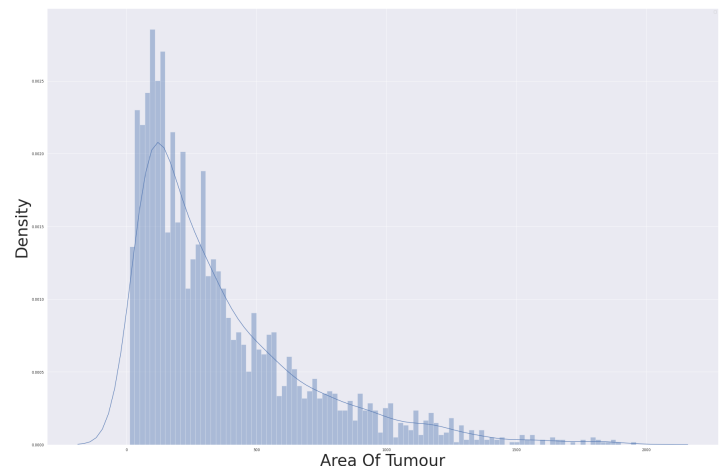

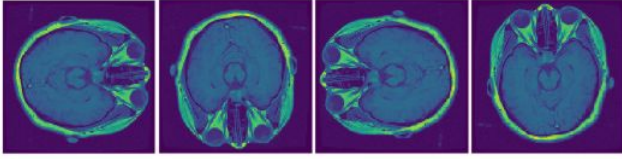FIGURE 2: This histogram represents the frequency of tumour having different area.

FIGURE 3: (a) The original Image (b) Image rotated 90 degrees (c) Image rotated 180 degrees (d) Image rotated 270 degrees
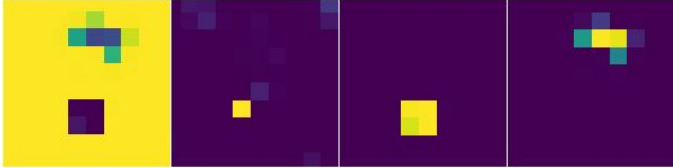

FIGURE 4: This figure shows the output when the 128x128 image is passed through model1. (Blue represents small values, yellow represents large values. Notice how blue region in one image represents yellow in other)

image of 128x128 with stride 2. If the tumour is completely present inside the convolution window, then it is added to the D2 with the label of tumour. If there is no tumour in the the convolution window, then it is added to the D2 with label 0 (label 0 corresponds to no tumour). The image which comes from the adjacent convolution windows have very redundant information. So, to control the size of the dataset we add each image to the new dataset with a some probability. The threshold for the probablity is taken to be 4%. The dataset D2 formed have unbalanced class. Under sampling method is used to make the classes balanced. Images are rotated in multiple of 90°and added to the dataset. Next, 70 % dataset is used for training and rest as test data.

IV. PROPOSED ARCHITECTURE

The model presented consists of two horizontally stacked models. The Two Deep Neural Networks are trained in parallel with combined 26 layers(say Network 1 and Network 2).Network 1 layer consists of 15 layers and the Network 2 consists of 11 layers. Both the networks are trained separately with Network 1 trained first. Network 1 is trained on the dataset D2 and classifies the input into one of the four classes meningioma, glioma , pituitary tumor and no tumor cell. The 128x128 image of the original dataset is passed through Network 1 to obtain 10x10x4 output with is used as input for Network 2. Then network 2 classifies the input into meningioma, glioma and pituitary tumor.

A. PROPOSED ARCHITECTURE FOR NETWORK 1

Figure 5 shows the proposed architecture for Model 1. It accepts image form dataset D2 and classifies it into 4 classes.

Type	Number of Filers	Kernel Size	Stride Value	Pad
Input	-	-	-	
Convolution	64	10x10	1x1	
ReLU	-	-	-	
Batch Normalization	-	-	-	
Max Pooling	1	2x2	2x2	
Convolution	128	3x3	1x1	
ReLU	-	-	-	
Max Pooling	1	2x2	2x2	
DropOut(probablity 0.10)	-	-	-	
Convolution	256	2x2	1x1	
ReLU	-	-	-	
Max Pooling	1	2	2x2	
DropOut(probablity 0.20)	-	-	-	
Convolution	12544	7x7	1x1	
ReLU	-	-	-	
Convolution	4	1x1	1x1	

TABLE 1: Architecture for Model 1.

B. PROPOSED ARCHITECTURE FOR NETWORK 2

Figure 6 shows the proposed architecture for Model 2. It accepts the output of model 1 as input and classifies it into 3 classes.

V. RESULTS ANALYSIS AND DISCUSSION
A. EXPERIMENTAL SETUP
B. EVALUATION CRITERIA
C. PERFORMANCE EVALUATION OF C-CADZ
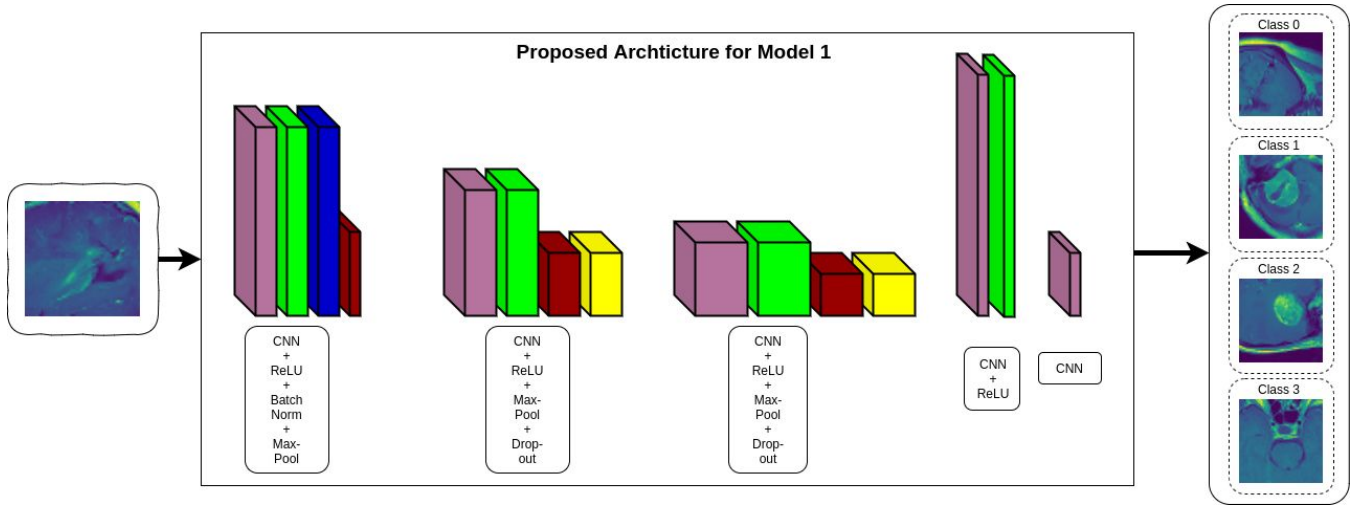## VI. CONCLUSIONS AND FUTURE WORK
REFERENCES
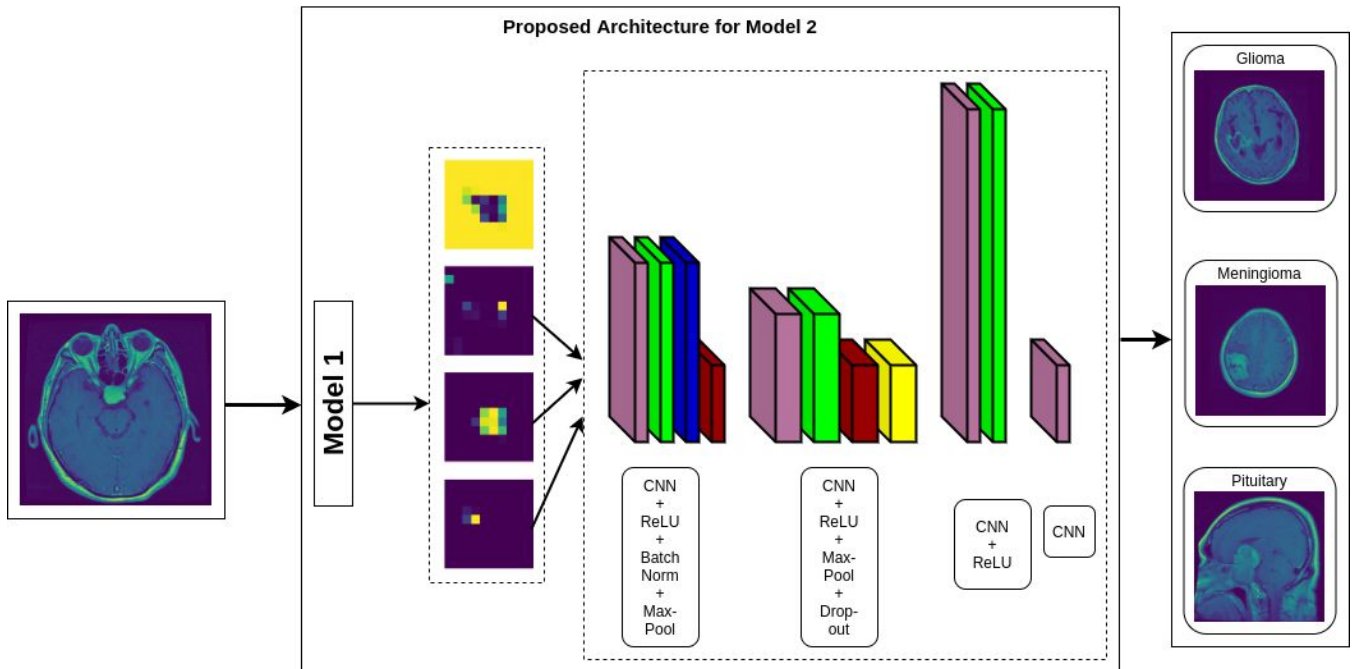
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FIGURE 5: Proposed Architecture for Model 1.

FIGURE 6: Proposed Architecture for Model 2.

| Type	Number of Filers	Kernel Size	Stride Value	Padding Value	Size of Output Layer	Total Parameters
Input	-	-	-	-	3x10x10	-
Convolution	32	2x2	1x1	2x2	32x13x13	416
ReLU	-	-	-	-	32x13x13	-
Batch Normalization	-	-	-	-	32x13x13	64
Max Pooling	1	2x2	2x2	-	32x6x6	-
Convolution	64	3x3	1x1	2x2	64x8x8	18,496
ReLU	-	-	-	-	64x8x8	-
Max Pooling	1	2x2	2x2	-	64x4x4	-
Dropout(probablity 0.1)	-	-	-	-	64x4x4	-
Convolution	1024	4x4	1x1	-	1024x1x1	1,049,600
ReLU	-	-	-	-	1024x1x1	-
Convolution	3	1x1	1x1	-	3x1x1	3,075

TABLE 2: Architecture for Model 2.
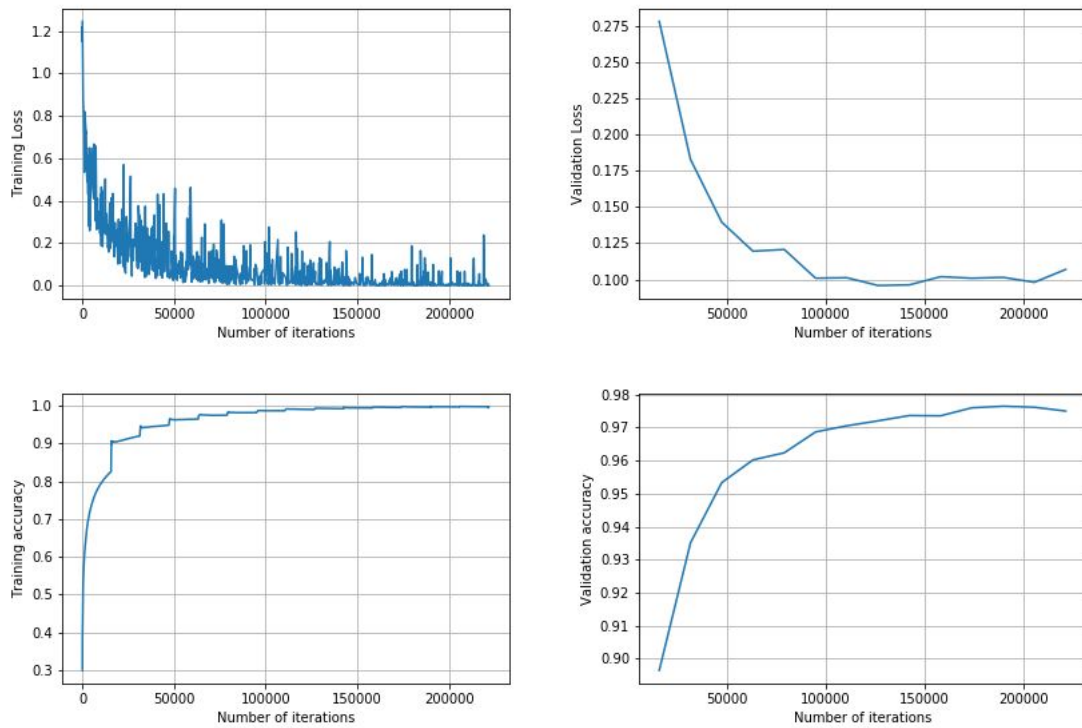
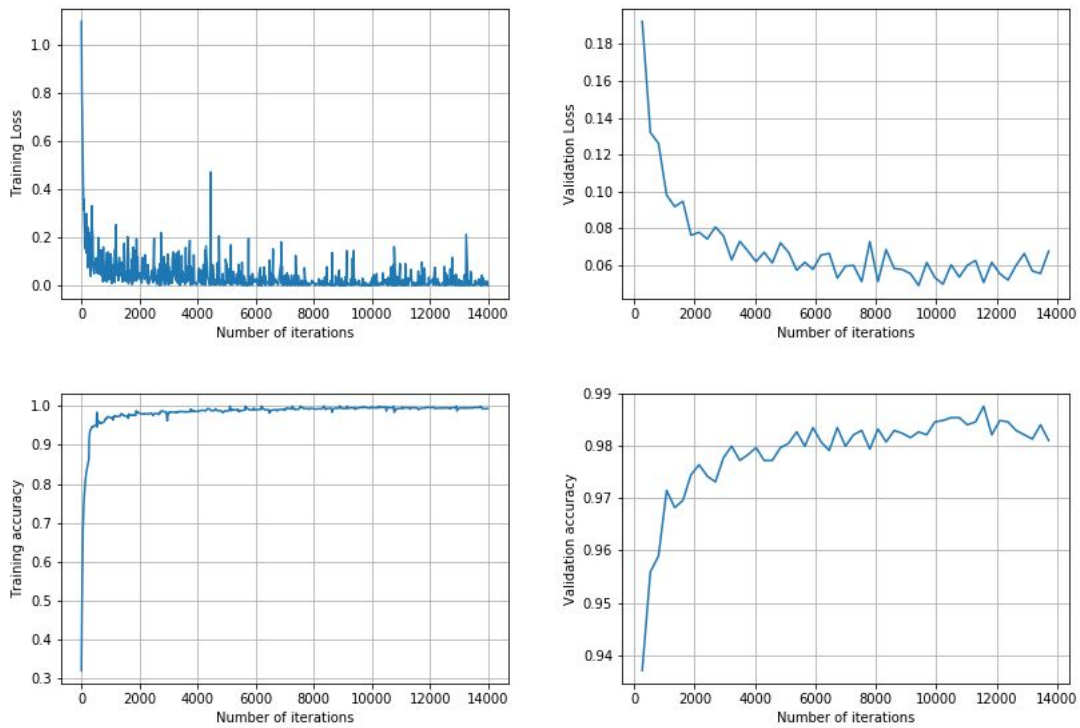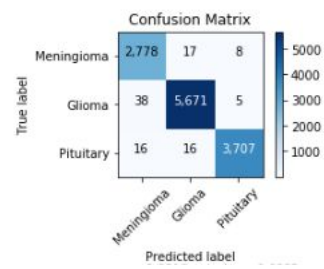FIGURE 7: Proposed Architecture for Model 1.

FIGURE 8: Proposed Architecture for Model 1.

FIGURE 9: Proposed Architecture for Model 1.