Digital Object Identifier

Classification of Brain Tumor Images Using Convolutional Neural Network

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ABSTRACT
Brain Tumor classification is a crucial step in treatment of brain tumors in medical science. Brain tumors are classified into 3 types named : meningioma, glioma and pituitary tumor. MRI is most commonly used imaging technique for detection of tumors due to better image quality. Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. In this paper, Deep Learning model based on CNN is proposed to classify brain tumor types using publicly available dataset. The dataset include T1-weighted contrast-inhanced images from 233 patient. The proposed network structure achieves a significant performance with best accuracy of 98.74 %.The results indicate the ability of the model for brain tumor multi-classification purposes.

I. INTRODUCTION
Main Contribution:

Brain tumour is cancerous or non-cancerous mass or growth of abnormal cells in the brain. In 2016, more than 200,000 people died due to brain tumour. Early detection of the tumour is crucial part in the treatment. In this paper we have build a model to classify brain tumour using a publicly available dataset.

The major research contributions can be listed as:

- The experiment show best accuracy of 98.74 % in multi class classification of brain tumor compared to previous papers listed in Table 3.
- It is found that as the effective relative area of the object to be classified increases as compared to the image size then the accuracy of classification increases.

The rest of the paper is organized as follows.

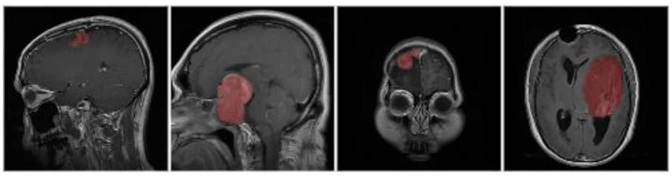

FIGURE 1: The maroon part shows the actual tumor cell. The four above given images show the variation of shape, size and position of the tumor present in the dataset.

II. 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 prepossessing 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 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

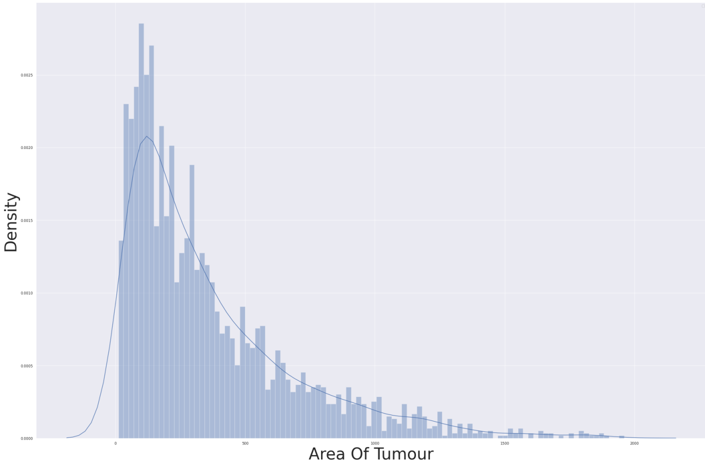

FIGURE 2: This histogram represents the frequency of tumour having different area.

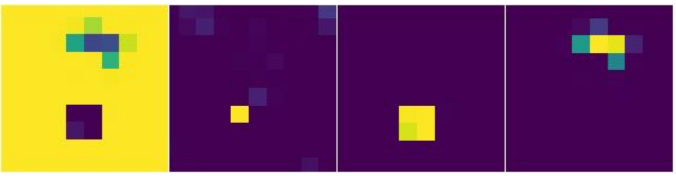

FIGURE 4: This figure shows the output when the 128x128 image is passed through model1. (Blue represents small values, yellow represents large values. Notice how blue region in one image represents yellow in other)

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 probability 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.

III. PROPOSED ARCHITECTURE

The model presented consists of two horizontally stacked models. The Two Deep Neural Networks

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

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

IV. RESULTS ANALYSIS AND DISCUSSION

Best Accuracy on Validation Set of Model 1 is 97.64 %. Best accuracy on Validation set of Model 2 is 98.74 %. The loss and accuracy graph for both the models are given in figure 7 and 8 respectively. The Model was trained using pytorch on RTX 2060 GPU and total training time was about 5 hours. All the code are available on github

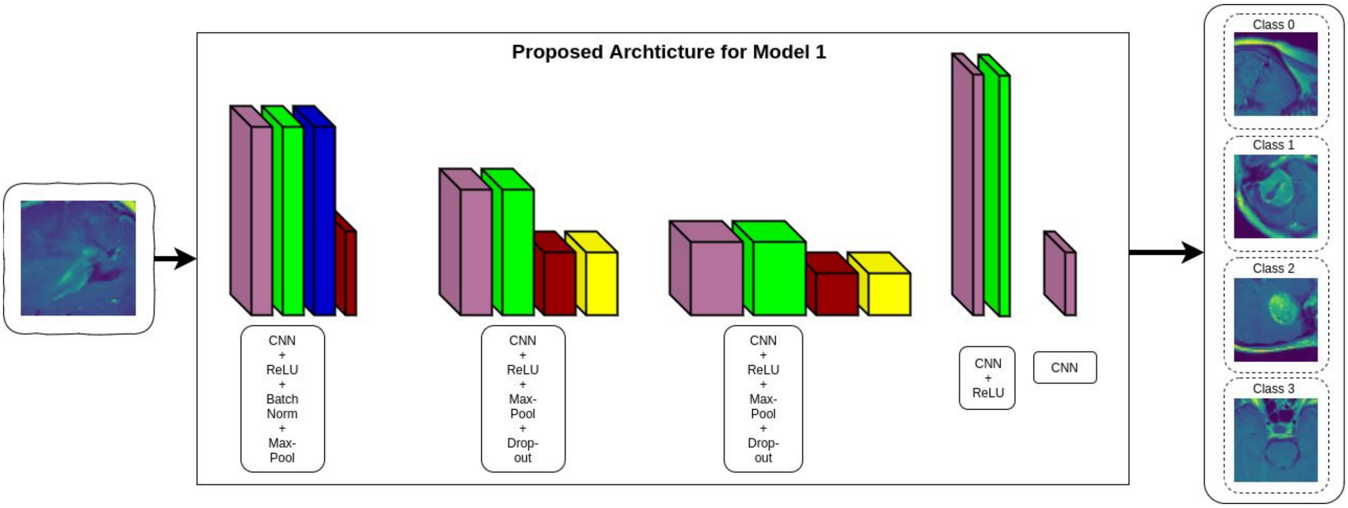

FIGURE 5: Proposed Architecture for Model 1.

Type	Number of Filers	Kernel Size	Stride Value	Padding Value	Size of Output Layer	Total Parameters
Input	-	-	-	-	1x50x50	-
Convolution	64	10x10	1x1	-	64x41x41	6,464
ReLU	-	-	-	-	64x41x41	-
Batch Normalization	-	-	-	-	64x41x41	128
Max Pooling	1	2x2	2x2	-	64x20x20	-
Convolution	128	3x3	1x1	2x2	128x22x22	73,856
ReLU	-	-	-	-	128x22x22	-
Max Pooling	1	2x2	2x2	-	128x11x11	-
DropOut(probablity 0.10)	-	-	-	-	128x11x11	-
Convolution	256	2x2	1x1	2x2	256x14x14	131,328
ReLU	-	-	-	-	256x14x14	-
Max Pooling	1	2	2x2	-	256x7x7	-
DropOut(probablity 0.20)	-	-	-	-	256x7x7	-
Convolution	12544	7x7	1x1	-	12544x1x1	157,364,480
ReLU	-	-	-	-	12544x1x1	-
Convolution	4	1x1	1x1	-	4x1	50,180

TABLE 1: Architecture for Model 1.

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.

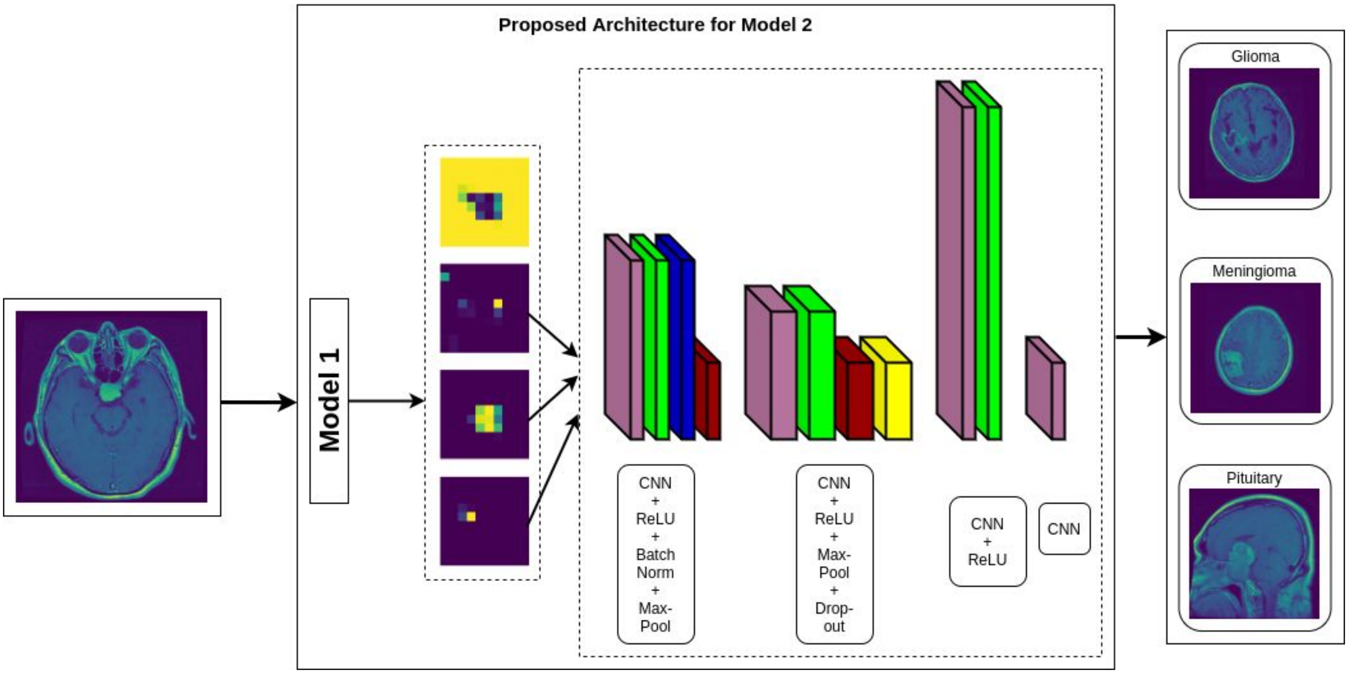

FIGURE 6: Proposed Architecture for Model 2.

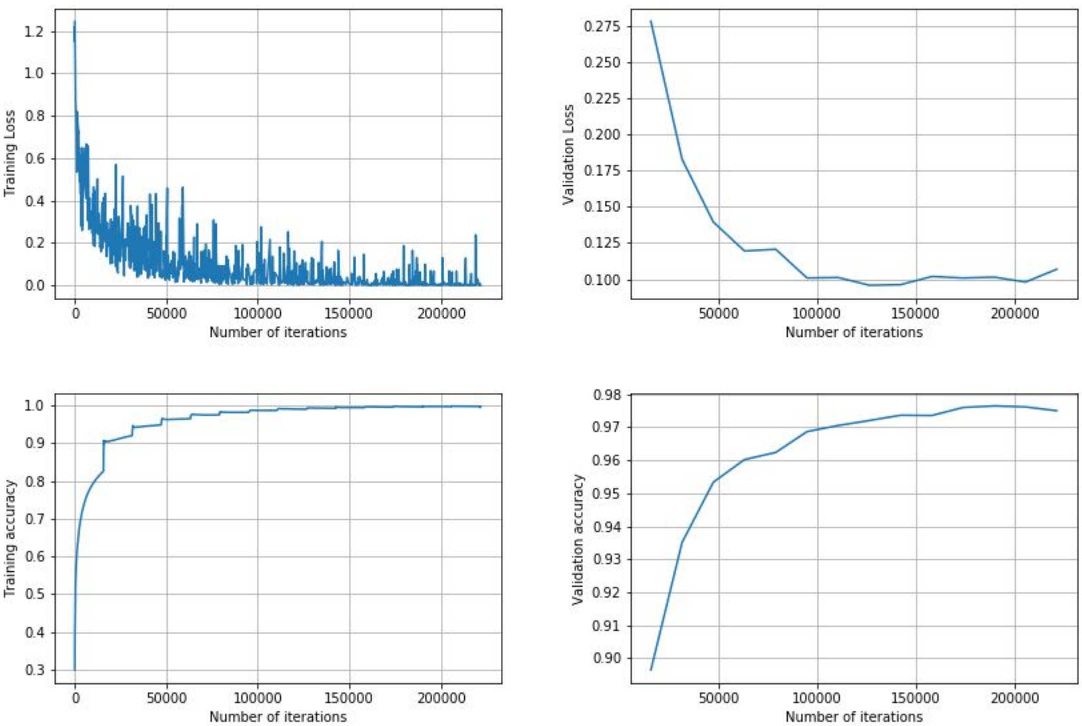

FIGURE 7: Proposed Architecture for Model 1.

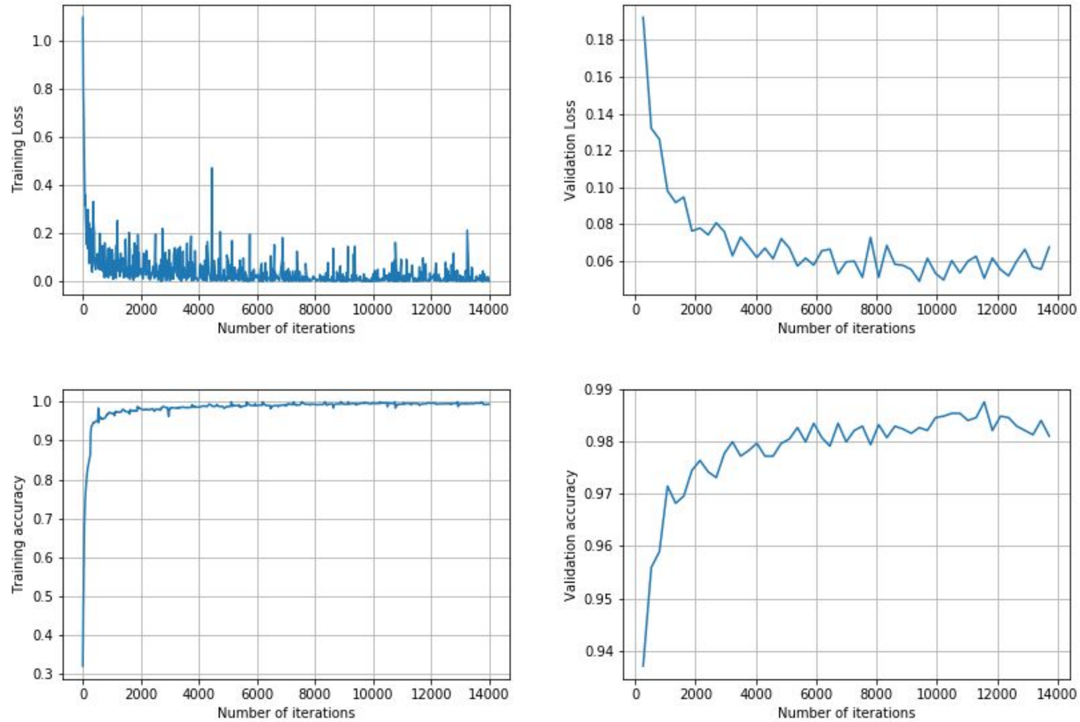

FIGURE 8: Proposed Architecture for Model 1.

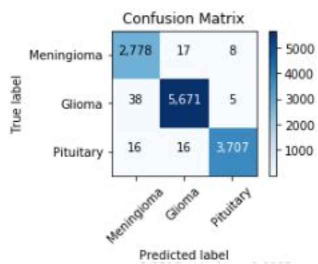

FIGURE 9: Proposed Architecture for Model 1.

	Paper	Best accuracy	Classification method
1	J. Cheng, W. Huang, S.Cao, R.Yang, W.Yang, Z. Yun, Z.Wang, and Q.Feng, “Enhanced performance of brain tumor classification via tumor region augmentation and partition,” PloS ONE, vol.10, no.10, Oct.2015, Art no e0140381.	91.28 %	SVM and KNN
2	J.S. Paul, A.J. Plassard, B.A. Landman, and D.Fabbri, “Deep learning for brain tumor classification,” Proc. SPIE, Med. Imag., Biomed. Appl. Mol., Struct., Funct. Imag., vol. 10137, Mar. 2017, Art. no. 1013710. doi: 10.1117/12.2254195	91.43%	CNN
3	J cheng P.Afshar, K. N. Plataniotis, and A.Mohammadi, “Capsule net- works for brain tumor classification based on MRI images and course tumor,” 2018, arXiv:1811.00597.	90.89%	CNN
4	A. K.Anaraki, M.Ayati, and F.Kazemi, “Magnetic resonance imaging based brain tumor grades classification and grading via convolutional neural networks and genetic algorithms,” Biocybernetics Biomed. Eng., vol. 39, no. 1, pp. 63–74, Jan./Mar. 2019.	94.2 %	GA-CNN
5	Multi-Classification of Brain Tumor Images Using Deep Neural Network HOSSAM H. SULTAN , NANCY M. SALEM , AND WALID AL-ATABANY	96.13%	CNN

TABLE 3: Latest papers published using the same dataset.