

Analysis of Brain Tumor Detection Using Machine Learning

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Abstract: Brain Tumor which is also known as intracellular tumor, contains abnormal mass of tissues in which cells grow uncontrollably, seemingly unchecked by mechanism which control normal cells. Astrocytoma, Glioblastoma, Oligodendroglioma are the types of tumor we have included in our dataset for analysis. We are going to use neural network based algorithm named Convolutional Neural Network for Classification purpose. In Section 1 Introduction about the tumor is represented, background is given in Section 2, Proposed method is described in Section 3, experimental results are given in Section 4, and finally Conclusion is given in Section 5.

Index Terms: Convolutional Neural Network, Astrocytoma, Glioblastoma, Oligodendroglioma, Rectified Linear Unit, Recall, Precision

I.INTRODUCTION

The abnormal growth of tissues in the brain or central spine that can disrupt proper brain function is known as Brain tumor. Doctors always refers about the tumors location and whether they are cancerous (Malignant) or Non-Cancerous (Benign). Benign is less aggressive, non-cancerous type of tumor as it has clear borders that do not spread into other tissue. Malignant which is life threatening, contains cancerous cells as they do not have clear borders. [1] One of the research of US has estimated that from around 680,000+ people having tumor, 138,000 have malignant tumors and 550,000 are suffering with benign tumor. From the cancerous tumor 16% of them have Glioblastoma, 7% of them have Astrocytoma, 35% have Meninglioma, 14% have pituitary, 9% have Nerve sheath, 2% have Lymphoma and 33% were other cancerous tumors like Ependymoma, Oligodendroglioma, Embryonal etc which all are types of malignant tumors. Tumors are represented by a name based on the cells where they arise, and a number ranging from 1–4. **Lower grade tumors** which comes under grades I & II are not very aggressive and are usually associated with long-term survival, **Higher grade tumors** (grade III & IV) grow more quickly, causes more damage, and are often more difficult to treat. These are considered malignant or cancerous.

Grade I Tumor contains Slow-growing cells almost normal appearance under a microscope, usually not cancer and are associated with long-term survival and can potentially be cured with surgery

Grade II Tumor are relatively slow-growing, slightly abnormal appearance under a microscope, can invade adjacent normal tissue, can recur as a higher grade tumor

Grade III Tumor contains actively reproducing abnormal cells of abnormal appearance under a microscope they are infiltrate adjacent normal brain tissue in this grade tumor tends to recur, often as a higher grade

Grade IV Tumor which contains abnormal cells which reproduce rapidly and are of very abnormal appearance under a microscope they form new blood vessels to maintain rapid growth and contains areas of dead cells (necrosis) in center.

Gliomas starts beginning from glial cells found in the supportive tissue of the brain. There are different types of gliomas, categorized by where they are found, and where the tumor begins. Astrocytomas begin in the supporting tissue cells (astrocytes). In adults, they are most commonly found in the cerebrum where they cause pressure, seizures and personality changes the below figure 1 shows the image of astrocytomas tumor, this tumor are generally subdivided into low (grade I & II) or high grade (grade III & IV). High grade (grade IV) are the most malignant of all brain tumors, known as glioblastoma given below in figure 2. Oligodendrogliomas tumor starts from the supporting cells of the brain, often found in the cerebral hemispheres (cerebrum), causing seizures, headaches, weakness, sleepiness, or changes in behavior. Oligodendrogliomas given as figure 3 in below image tend to respond better to therapies and have a better prognosis than most other gliomas. They are grade II or III.

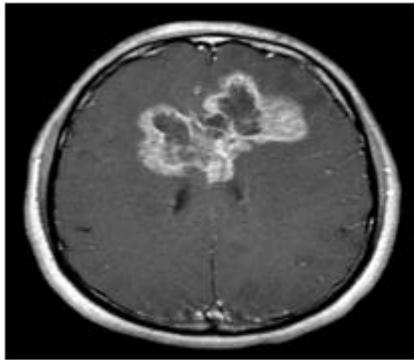


Figure 1: Astrocytoma tumor

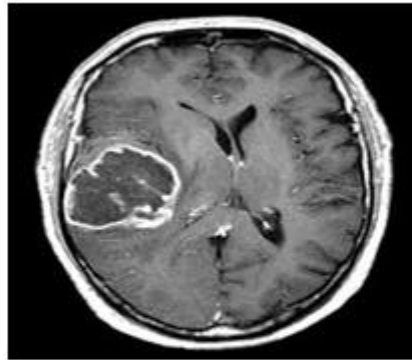


Figure 2: Glioblastoma tumor

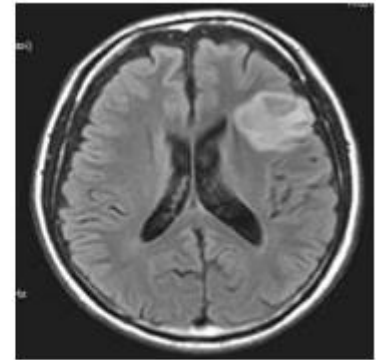


Figure 3: Oligodendroglioma tumor

Scanning is the first step for identifying a brain tumor's Location and growth. Commonly used scanning and imaging techniques are Computed Axial Tomography (CAT or CT scan) is a computerized x-ray shows a combination of soft tissue, bone, and blood vessels. Magnetic Resonance Imaging (MRI) creates clear and detailed three-dimensional images of a brain tumor. An MRI is not often used with people who have a pace maker or other metal device, Magnetic Resonance Spectroscopy (MRI Spect or MRS), measures the levels of metabolites in the body. MRS another technique of scanning helps to detect irregular patterns of activity to help diagnose the type of tumor, evaluate its response to therapies, or determine aggressiveness of a tumor. Positron Emission Tomography scan it uses a radioactive substance to visualize hyper metabolic activity such as with malignant cells, or abnormalities from a tumor or scar tissue. PET is also used during brain mapping procedures, Spinal tap (also called a lumbar puncture), uses a special needle placed into the lower back to measure pressure in the spinal canal and brain which determines if there is an infection or tumor cells. As, this all scanning techniques takes time and doctor's have to take multiple scans over time: first to detect the tumor; then to observe the site after surgery; later, with follow-up care, to see if the tumor returns, this fact increases the researchers importance on the tumor detection.

II. BACKGROUND

2.1 Convolutional Neural Network :[2] With the labeled SAR images provided by the GF-3 satellites, proposes a convolutional network (MT-CNN) to classify marine targets at patch level and an overall scheme for detecting the different marine targets in large-scale SAR images. The proposed MT-CNN with six convolutional layers and three pooling layers are capable of extracting features at different levels and achieve higher classification accuracy than existing CNN models. As for the marine target detection task in large-scale SAR images, the proposed MR-SSD with a three-resolution input is able to learn the features on different resolution versions. The proposed framework containing sea-land segmentation, cropping with overlapping, Detection with MR-SSD model, and coordinates mapping shows its superiorities to other methods by improving detection accuracy and reducing false alarms. Besides, this is the first such experiments that carry out on such various types of marine targets in SAR images. This paper presents the preliminary results of the proposed methods. Looking ahead, future works can be focused on eliminating false alarms in SAR imageries by image processing methods.[4]An approach based on CNN was proposed for vehicle detection and classification for more accurate classification unrelated background was removed as much as possible, an unsupervised pretraining approach was introduced for better classification performance .[5] address object identification and recognition in the wild for infrared (IR) imaging for defense applications, where no such large-scale dataset is available. With a focus on robustness issues, especially viewpoint invariance, here a compact and fully convolutional CNN architecture with global average pooling is introduced. The model trained from realistic simulation datasets reaches a state-of-the-art performance compared with other CNNs with no data augmentation and fine-tuning steps.

2.2 Deep Neural Network : A neural network having more than one hidden layer is generally referred to as a Deep Neural Network. [6] Deep learning is a powerful machine learning technique that automatically learns image features for training robust object detectors. There are several techniques for object detection using deep learning such as Faster R-CNN and you only look once (YOLO) v2.

III. PROPOSED ALGORITHM

Proposed model for brain tumor classification is given below:

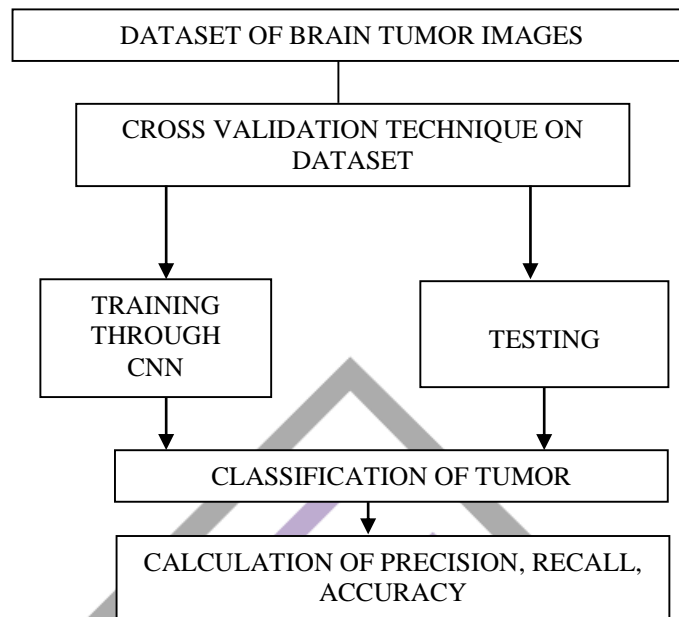


Figure 4: Proposed method for finding Brain Tumor Classification

3.1 DATASET:

The dataset used in the study were taken from [7],[8],[9] the data was gathered from three different sources and was combines to a single file using Numpy..In dataset the images were in .pk1 file format. Used astrocytoma, glioblastoma, Oligodendroglioma, Healthy brain MRI, Unidentified tumor. All the programs codes were written in python 3.5.The below table shows the classification of dataset containing data source, tumor type, number. of images .

Data source	Tumor type	No.of Images
REMBRANDT	Astrocytoma	21307
	Glioblastoma	17983
	Oligodendroglioma	12460
	Unidentified	13677
MIRIAD	Healthy brain	30688
BRAINS		556
Total		96115

Table: 1 Dataset Description

3.2 CROSS VALIDATION TECHNIQUE:

We have used k-fold cross-validation method to perform cross-validation. In k-fold cross-validation, you split the input data into k subsets of data known as folds. The model was trained on all but one (k-1) of the subsets, and then evaluate the model on the subset that was not used for training. This process is repeated 6 times, with a different subset reserved for evaluation each time the training part is excluded. The problem of over fitting which occurs due to very specific or extra features or attributes given to model while

training and another problem Under fitting which occurs when we give less features and attributes to train the model can overcome through the validation technique .

3.3 TRAINING AND TESTING IN CNN:

Convolutional neural network is a neural network that takes more than one convolutional layer; a convolution layer is sliding a filter over the input image. The combination of convolutional layer and pooling together makes a hidden layer, as the number of hidden layers increases the network starts becoming deeper and that is called a deep neural network.

In my project I have considered 64x 64x3 images which represented 5 classes as was represented above in dataset description. In our CNN architecture we have used 4 convolutional layer and Max pooling, 2 Fully Connected layers and a drop out layer which switches off some neurons in the network which forces the data to find new path and it also reduces over fitting. Input concatenation is done in this architecture, we have provided the first CNN’s output directly as input to the second CNN. They are thus simply treated as additional image channels of the input patch. We then compile the model using a cross entropy loss function, Adadelta optimizer and accuracy metric. We then fit the dataset to model for 100 epochs. After training of the model , we evaluate the loss and accuracy of the model on the test data and print it.

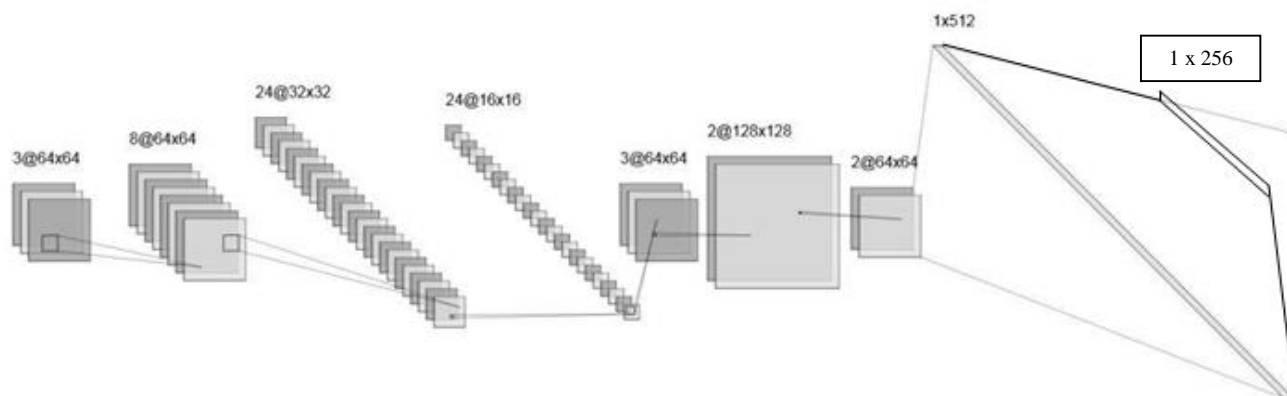


Figure 5: CNN Architecture Model

IV. EXPERIMENTAL RESULTS

The validation accuracy is calculated through the coding and we can find precision and recall . In our output we have got Confusion matrix through which we can calculate both precision and recall. Precision tells us how much percentage of positive identifications are actually correct.

$$\text{Precision} = \frac{TP}{TP+FP}$$

Were, [3]TP is the number of abnormal tumor images found as abnormal, T N is the number of normal tumor images found as normal, FP is the number of normal tumor images found as abnormal (false positives) and FN is the number of abnormal tumor images found as normal (false negatives).

Now, we need to calculate Recall which tells us about how many actual positives was identified correctly.

$$\text{Recall} = \frac{TP}{TP+FN}$$

	CLASS 1	CLASS 2	CLASS 3	CLASS 4	CLASS 5	Classification Overall	Precision
CLASS 1	21304	0	3	0	0	21307	99.986%
CLASS 2	2	17979	2	0	0	17983	99.978%
CLASS 3	0	0	12460	0	0	12460	100%
CLASS 4	0	0	0	30688	0	30688	100%
CLASS 5	0	0	0	0	13677	13677	100%
Truth Overall	21306	17979	12465	30688	13677	96115	
Recall	99.991%	100%	99.96%	100%	100%		

Table 2: Representation of Precision and Recall of individual class

The overall accuracy is 99.993%

V CONCLUSION

The proposed method can be used for tumor detection and to know how to check whether the obtained output is accurate or not. CNN which is one of the deep learning methods, which contains sequence of feed forward layers. The training is performed for only final layer. Also raw pixel value with depth, width and height feature value are extracted from CNN. The training accuracy, validation accuracy, precision, Recall is calculated . The test dataset and whole dataset accuracy is found to be 99.9% .

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