Brain Tumor Detection Using Deep Learning and Image Processing

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Abstract: *Brain Tumor Detection is one of the most difficult tasks in medical image processing. The detection task is difficult to perform because there is a lot of diversity in the images as brain tumors come in different shapes and textures. Brain tumors arise from different types of cells and the cells can suggest things like the nature, severity, and rarity of the tumor. Tumors can occur in different locations and the location of tumors can suggest something about the type of cells causing the tumor which can aid further diagnosis. The task of brain tumor detection can become aggravating by the problems which are present in almost all digital images eg. illumination problems. Tumor and non-tumor images can have overlapping image intensities which makes it difficult for any model to make good predictions from raw images. This paper proposes a novel method to detect brain tumors from various brain images by first carrying out different image preprocessing methods ie. Histogram equalization and opening which was followed by a convolutional neural network. The paper also discusses other image preprocessing techniques apart from the ones that are finalized for training and their impact on our dataset. The experimental study was carried on a dataset with different tumor shapes, sizes, textures, and locations. Convolutional Neural Network (CNN) was employed for the task of classification. In our work, CNN achieved a recall of 98.55% on the training set, 99.73% on the validation set which is very compelling.*

Keywords— *Brain Tumor Detection, Computer-aided Diagnosis, Computer Vision, Convolutional Neural Networks, Deep Learning, Image Processing, Transfer Learning.*

I. INTRODUCTION

A Brain Tumor is a mass of tissue in which the cells multiply uncontrollably. It arises from different cells - both in the brain and outside. Primary tumors are the ones that originate in the brain itself whereas secondary tumors are the ones that metastasize to different parts of the body. Tumors can have different origins and based on the cells or the origin obtained from different types of tumors. For example, gangliogliomas are tumors that include neoplastic neurons and are mostly grade I or low-grade tumors which indicates that the tumor is well-differentiated and has slow growth [16]. Another example is meningioma which originates from the meninges (The set of 3 membranes covering the brain and spinal cord) and can be grade I, II, or III and it is slow-growing [16]. Symptoms of a brain tumor include headache which can be acute and persistent, muscular disorders, dizziness, cognitive disorders, etc. Treatment of the same includes chemotherapy, radiotherapy, tomotherapy, and surgery (craniotomy). Although brain tumor is comparatively infrequent ie. 1.4% new cases per year [17], in developed countries, fatalities due to brain tumors have increased over the past few decades. CNS tumor cases in India range from 5 to 10 per 100,000 population with an increasing trend and it accounts for 2% of malignancies.

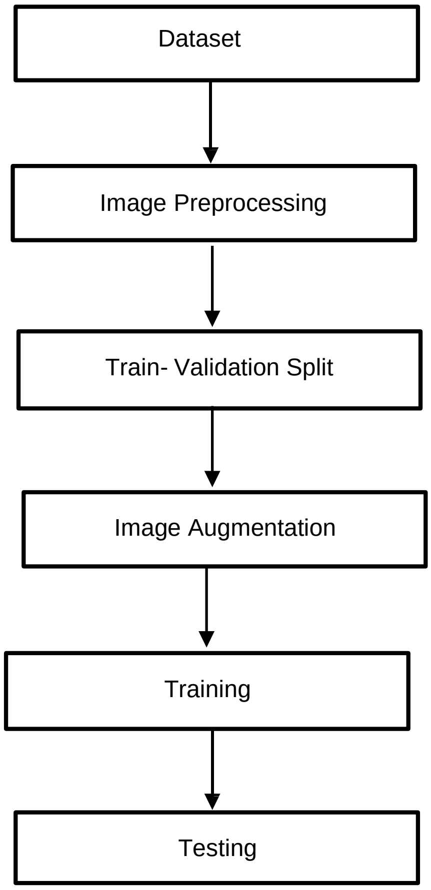
In recent times, Computer-aided diagnosis of diseases is gaining interest and is helping doctors take swift decisions. One such approach is using Convolutional Neural Networks (CNN) to learn the spatial and temporal features from the given dataset which are necessary to identify the disease. A Convolutional Neural Network is a special type of neural network which specializes in handling image datasets. The very fundamental principle of this neural network is performing a convolution operation between the kernel and the image to extract the features. All neural networks learn by the iterative updation of the weights matrix. Here, it is required to find the optimal kernel values for all layers of the CNN model. Hence, the kernel values themselves act as the weights of this model and the optimal values of the kernel are gradually learned through backpropagation and gradient descent. Backpropagation is the computation of derivatives of the loss function with respect to the weights and biases in a backward fashion. Gradient descent is the periodic updation of the weights such that the loss or the error is decreasing with each iteration. A convolutional layer is often coupled with a pooling layer and we can connect multiple such convolutional layer-pooling layer pairs. In the end, we can have few Dense layers and dropout layers for the final learning process. Dropout layers are used for tackling the overfitting problem. The last output layer does the classification job and can have only 1 neuron in case of a binary classification task or more than 1 for a multi-class classification task. Special types of neural networks called Capsule networks which encode the spatial information well along with the probability of the object being there in the image are gaining popularity and they are used in some recent works.

Brain tumors in MRI scans (or any other scans) are identified by abnormal blobs in the brain. These blobs or regions have a different illumination than the rest of the brain and are usually brighter than the background. However, the process of segmenting the tumors in MRI images is a very difficult task. The tumors have different sizes, textures, and even the positions where they are found. If we consider segmenting the tumor by properties such as illumination, we may face issues such as overlapping pixel intensities with the normal tissues. Identification and segmentation of brain tumors in MRI images is important as it indicates the presence of the abnormal tissues for treatment or patient follow-up purposes. Most brain tumors also cause edema [14] which is also a factor that distorts the nearby structures and can change the pixel intensities around the tumor. CNN along with some preprocessing techniques can give accuracy comparable to or even higher than humans. In this paper, we have presented a novel brain tumor detection method in MRI images. The first step was image preprocessing involving morphological techniques as well as histogram equalization to enhance our dataset. Then, thetumor and non-tumor image classification is carried out using the Convolutional Neural Network (CNN). This paper strongly emphasizes the use of image processing as digital images suffer from various problems such as the illumination problem discussed above and so without proper image preprocessing techniques, even CNNs can get misguided to learn incorrect features and produce wrong outputs. It is also necessary that we choose the right techniques because a major problem with image processing for datasets is that the chosen technique might be beneficial to only a particular type of image instead of generalizing well to the entire dataset. As such, while experimenting with the techniques, we found some techniques to be harmful to the dataset even before fitting a model to it while some techniques looked promising and so we decided to go ahead with the training process.

In this paper, we start by discussing the methodology we used – ie starting from the dataset followed by discussing the effects of different image processing techniques on the dataset and then preparing the proper dataset format for training, image augmentation, and training and through the performance metrics to the result and conclusion.

II. METHODOLOGY

Block Diagram



Data Set

The input dataset was mostly made up of a subset of a dataset[1] consisting of 3762 tumor images and the subset contained 2297 images. The subset selection was done based on removing the images which might have misdirected the model training. Another small dataset of 253 images was added[2]. This dataset has 155 tumor images and 93 nontumor images. For more non-tumor images, all 105 non-tumor images from another dataset were used[3]. The non-tumor images folder was named "no_tumor" in the original dataset on Kaggle. The images were preprocessed and then a 70%-30% split was performed to get the training and validation dataset. The preprocessing which was applied consisted of histogram equalization followed by opening. The resultant dataset was upsampled to get the final dataset of 4222 images consisting of 1861 training tumor images, 563 training non-tumor images, 1463 validation tumor images, and 315 validation non-tumor images. Upsampling was done as the dataset should be large enough for the model. Test Dataset consists of 20 randomly picked images from the internet out of which 10 had tumors and 10 didn't.

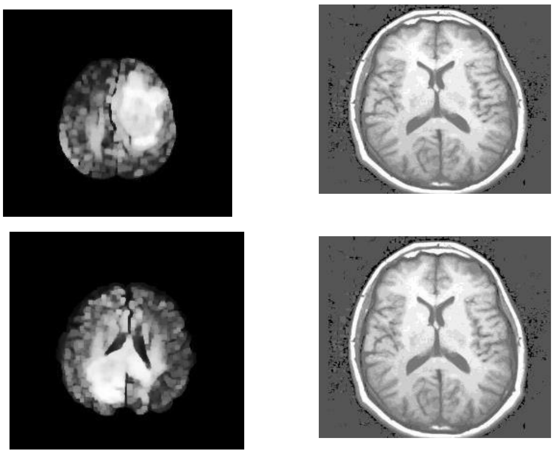
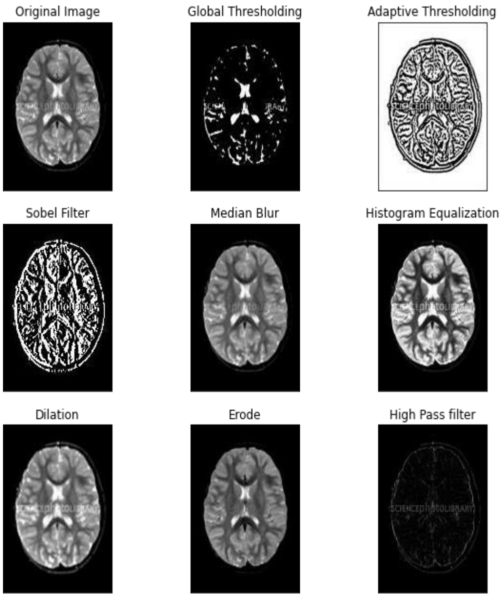
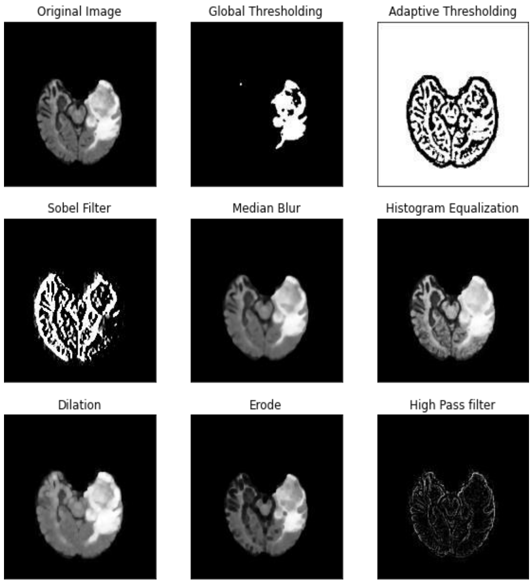


Image processing





III. RELATED WORK

Global Thresholding:

This method proved to be quite ineffective. The reason being, the different levels of illumination,i.e the different pixel intensities in different images. Thus, a global threshold cannot be chosen for all the images, because of their different pixel intensities. In the tumor images, the tumor is brighter than the rest of the brain area. If we set a threshold value, which separates the bright tumor portion and the darker brain portion, it disrupts with some nontumor images in which the entire brain portion is bright. Setting a threshold will classify these nontumor images as tumor images, hence proving to be ineffective. See figure 7 where global thresholding makes the brain MRI image look like there is a tumor but the true label states otherwise.

Adaptive Thresholding:

Adaptive thresholding does not use a fixed threshold value for all pixels in the image. Instead, the threshold is calculated based on the range of intensities in the pixel's local neighborhood. Therefore, different regions of the image will have different threshold values. This allows the thresholding to be done dynamically for different images. We can observe from the adaptive thresholding output that the outlines are highlighted. The issue is that even in the area of the tumor, the outlines are about equally abundant as there are in non-tumor regions. This makes it difficult to distinguish the tumor from the rest of the brain.

Sobel filter

Sobel filter is an edge detection filter and consists of a pair of convolutional kernels. The first of the pair detects edges running in the vertical direction while the other detects edges running in the horizontal direction. Sobel Filter Kernels This technique has a tragic effect on the images. The Sobel filter leads to the introduction of unwanted noise resulting in ample false detections. Hence this technique proved to be completely ineffective.

-1	0	+1
-2	0	+2
-1	0	+1

Gx

+1	+2	+1
0	0	0
-1	-2	-1

Gy

Sobel Filter Kernels

High Pass filter

A 3x3 high pass filter kernel consisting of 8 in the center and -1 everywhere else is applied to the images. Since it is a derivative filter, it highlights the edges and turns the background black. Here it does a similar job and in doing so, we make the tumor indistinguishable from the background which is a tragic effect. So we cannot use this technique for our task.

Median Blur

The median filter is good at eliminating Salt and Pepper noise. It does so by replacing the central values of the window of the image under consideration with the median of all the values in that window. Since the pixel intensities of the salt and pepper noise pixels are on the extreme ends ie. around 0 for black and around 255 for white in an 8 bit image, while computing the median, they lie on the extreme ends of the list of pixel intensities (arranged in ascending order for median computation) of a window. Therefore they rarely become the median and the non-noise pixels become the central value; eliminating the noise pixels. Here we observe that the edges and boundaries are preserved. Here very little difference is observed between the original and preprocessed image. Hence it is not very effective.

IV. PERFORMANCE METRICS

a. Performance metrics measure the performance of a model based on the predictions made v/s the true labels. The 3 metrics were accuracy, precision, and recall. F1 score is another metric that makes use of precision and recall.
b. Accuracy is the percentage of correctly classified data points. Accuracy is not a good metric as it fails to suggest anything in the case of imbalanced classes. Consider 10 images out of which 9 are tumor images and 1 is a non- tumor image. If the model learns badly and predicts every image as tumor images, then also the accuracy would be 90% in this case which is good on paper but it fails to tell us that the model was bad.

c. Precision is a metric that says out of all the images which the metric classified as tumor images, how many of those were tumors. Suppose the model identifies an image to be a tumor image, the person can consult a doctor to check if there's a tumor. In this case, there is no health risk ie in case of a false positive, the person will only have to spend that extra money and time for consulting a doctor.
d. Recall says that of all tumor images, how many of those did the model predict that there is a tumor. This is an extremely important metric and the one we will focus on in this task. Suppose if a person had a tumor,and

the model classifies it as non-tumor. The person would not consult a doctor and could die due to the lack of attention given to that case. Health risk increases if the model predicts a false negative.

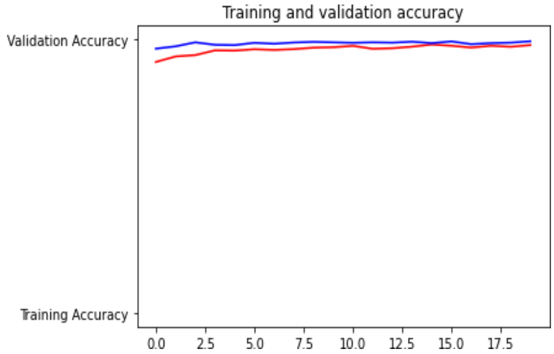
e. F1 score is a metric that conveys the balance between precision and recall. It is the harmonic mean of precision and recall and penalizesthe model a lot even when only one of them is low.

$$precision = \frac{TP}{TP + FP}$$

$$recall = \frac{TP}{TP + FN}$$

$$F1 = \frac{2 \times precision \times recall}{precision + recall}$$

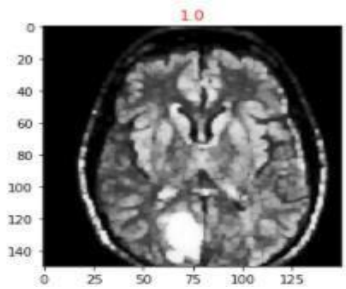
$$accuracy = \frac{TP + TN}{TP + FN + TN + FP}$$



We trained our CNN model for 20 epochs and we recorded the performance metrics after the 20th epoch.
The high values of the performance metrics are indicators of a well-trained model for the given dataset and the absence of underfitting which is good. The recall seems to be lower for the test set than on the validation set which can be attributed to the fact that the model was trained on a dataset of MRI images of a particular distribution while random images from the Internet might not necessarily belong to that distribution so the test data can be completely foreign to our database.

We also have the graphs below depicting the metrics values associated with the training and validation sets after each epoch. This can show the entire learning process of the model and even the presence of overfitting or underfitting (if any).

From the graphs, we can observe that the training process was smooth and the less gap between the training and validation lines, indicates high generalization to the validation images and absence of overfitting. The test images were plotted and we could see which images were correctly labeled and which were not.



V. RESULTS AND DISSCUSSION

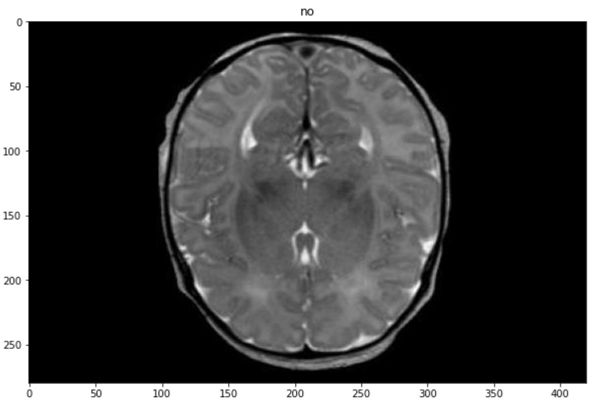
Path Processing:

If a brain tumor is suspected, imaging studies like MRI (Magnetic Resonance Imaging) or CT (Computed Tomography) scans are conducted to visualize the brain and identify any abnormal growths. To confirm the diagnosis, a biopsy is often performed. This involves surgically removing a small sample of the tumor tissue. The tissue is then examined under a microscope by a pathologist to determine the type of tumor and its grade (how aggressive it is).

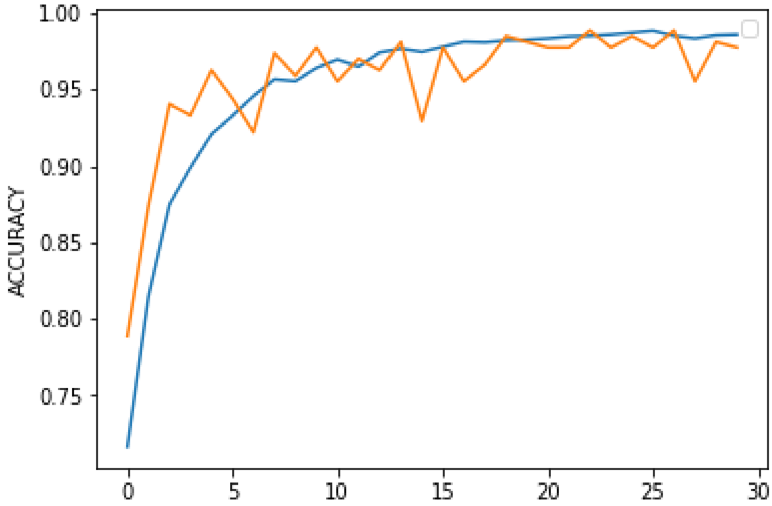
	JPG	TUMOR_CATEGORY
0	../input/brain-tumor-detection/no/no26.jpg	no
1	../input/brain-tumor-detection/no/no979.jpg	no
2	../input/brain-tumor-detection/no/no598.jpg	no
3	../input/brain-tumor-detection/no/no141.jpg	no
4	../input/brain-tumor-detection/no/no715.jpg	no
...	...	...
2994	../input/brain-tumor-detection/yes/y136.jpg	yes
2995	../input/brain-tumor-detection/yes/y1379.jpg	yes
2996	../input/brain-tumor-detection/yes/y1452.jpg	yes
2997	../input/brain-tumor-detection/yes/y378.jpg	yes
2998	../input/brain-tumor-detection/yes/y178.jpg	yes

Visualization:

After initial treatment, regular follow-up appointments and imaging studies are necessary to monitor for any signs of tumor recurrence or progression. Long-term monitoring is crucial for managing the patient's health and addressing any late effects of treatment.



Graphs:



VI. CONCLUSION AND FUTURE SCOPE

Conclusion:
The detection of brain tumors has significantly advanced due to improvements in imaging technologies, such as MRI and CT scans, which provide high-resolution and detailed visualizations. The incorporation of artificial intelligence (AI) and machine learning (ML) further enhances detection by analyzing vast imaging data, identifying subtle tumor characteristics, and improving diagnostic accuracy. Molecular and genetic profiling has also contributed to better understanding and identifying brain tumors. Techniques like next-generation sequencing reveal specific genetic mutations, enabling personalized treatment approaches.

Future Scope:
The future scope of brain tumor detection using Convolutional Neural Networks (CNNs) is highly promising, with several potential advancements on the horizon. CNNs, a class of deep learning algorithms, have already shown remarkable success in medical imaging due to their ability to automatically learn and extract features from complex datasets.

The detection of brain tumors has significantly improved with advanced imaging technologies like MRI and CT scans, offering high-resolution visuals. AI and machine learning enhance detection by analyzing large datasets to identify subtle tumor features, improving diagnostic accuracy. Molecular and genetic profiling further aids in understanding tumor characteristics, enabling personalized treatment.

These combined advancements allow for earlier and more precise detection, crucial for better patient outcomes through timely and targeted interventions. Despite these improvements, challenges remain in ensuring widespread access and integration of these technologies into clinical practice.

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