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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[11][12][13].

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 [18][19].

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

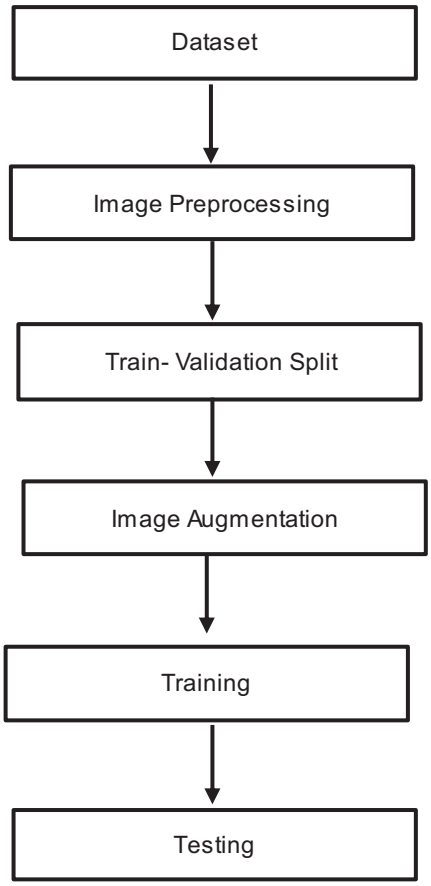
of the abnormal tissues for treatment or patient follow-up purposes. Most brain tumors also cause edema [14] which is also a factor that distorts the nearby structures and can change the pixel intensities around the tumor. CNN along with some preprocessing techniques can give accuracy comparable to or 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, the tumor 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

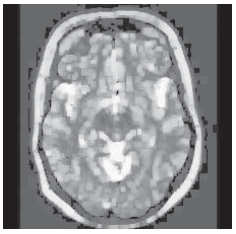
A. Block Diagram



B. Dataset

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 non-tumor 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.

1. 

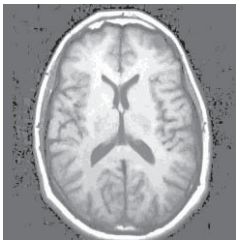
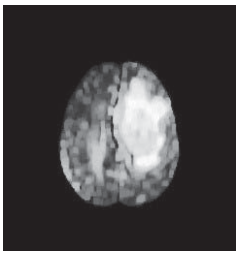
2. 

Figure 1 and 2: Sample non-tumor images from dataset.

3. 

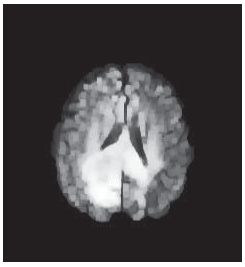
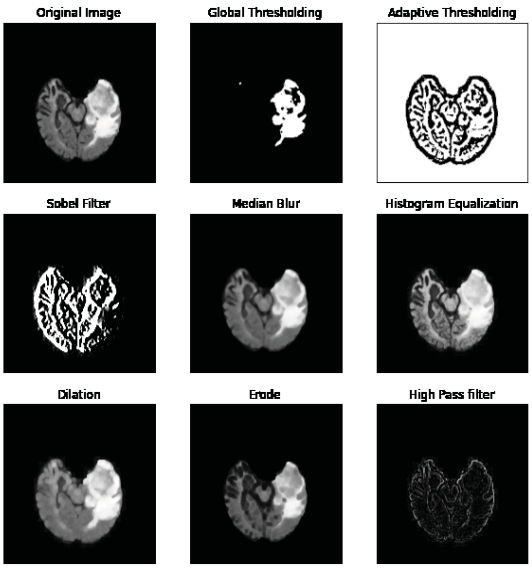
4. 

Figure 3 and 4: Sample tumor images from dataset.

C. *Image Preprocessing*

5. 

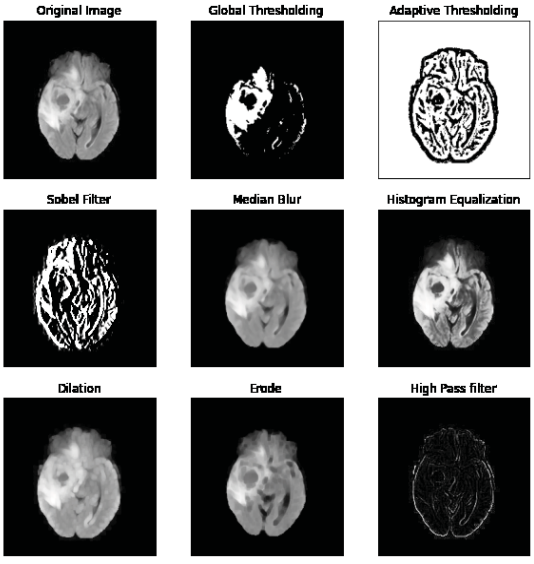
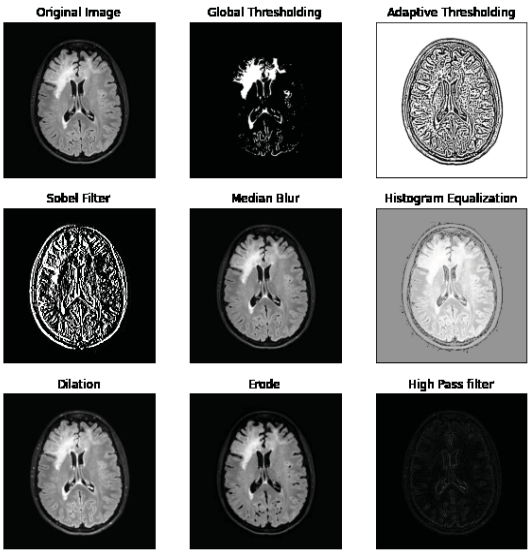
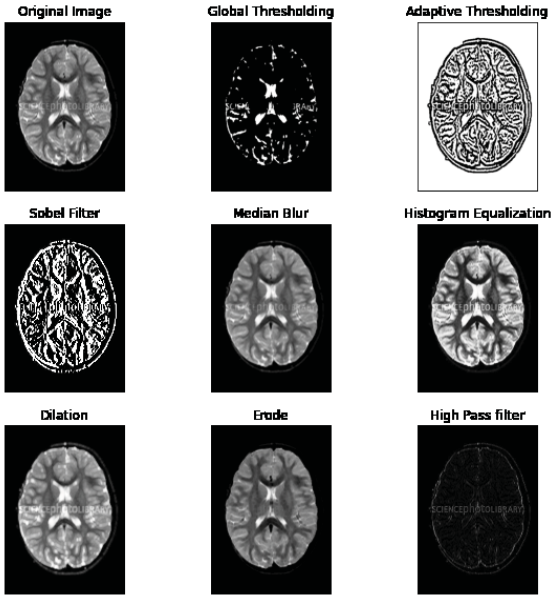
6. 

Figure 5 and 6: Image Processing on tumor images



7.



8.

Figure 7 and 8: Image Processing on non-tumor images

1. 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 non-tumor images in which the entire brain portion is bright. Setting a threshold will classify these non-tumor 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.

2. 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.

3. 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.

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

Gx

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

Gy

Figure 9: 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.

4. 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.

5. 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.

6. Histogram Equalization
This preprocessing method results in an overall improvement. This is because histogram equalization normalizes the pixel intensities, thereby normalizing some of the illumination problems. The technique does a great job in normalizing the pixel intensities of the brain MRI image in figure 7. The image belongs to the non-tumor class but the whiter patch on the top left part of the brain looks like a tumor although it is not. Histogram equalization reduced the visual difference between that area and the rest of the brain. This was an encouraging result and we can proceed to fit a Convolutional Neural Network (CNN) model on histogram equalized images.

7. Dilation
Dilation is an image preprocessing technique which adds pixels to the boundaries of objects. White regions such as tumors grow in size after dilation due to the addition of white pixels on the boundaries and the gaps in the white regions get filled as well (See the tumor region in Figure 6). If we take a structuring element of size 3x3 containing all 1s and we convolve on our image, any background pixel that is surrounded by at least 1 white pixel, will get changed to foreground pixel. Thus there is an overall decrease in darker regions and an increase in the whiter regions thus highlighting the tumor more. This technique looks promising and we will proceed with this image processing technique as well.

8. Erosion
Erosion works opposite of dilation as it removes the pixels from the boundaries of the objects. White regions such as tumors shrink in size after erosion and the gaps and holes in the white regions increase in size. If we take a structuring element of size 3x3 containing all 1s and we convolve on our image, any foreground pixel that isn't surrounded everywhere by white pixels, will get changed to background pixel. This can lead to the tumors (the main focus of our work) being played down. Although at first thought, erosion seems to be bad for this job, erosion combined with dilation (opening or closing) can prove to be effective**.** Opening (erosion followed by dilation) removes the small objects from the foreground which can be used to put the focus on the tumor region. Closing (dilation followed by erosion) removes the small gaps and holes in the foreground which can be used to eliminate the darker central regions of the tumor.

Conclusion: Histogram Equalization, erosion, and dilation were the promising techniques for this task and we tried different combinations of these for the preprocessing pipeline.
Training on histogram equalized images gave an accuracy of 98% on the train set and 80% on the test set which suggests overfitting.
Training on opened (erosion and dilation) images gave an accuracy of 96% on the train set and 84% on the test set.
Training on histogram equalized and closed (dilation and erosion) images gave an accuracy of 96% on the train set and 84% on the test set.

The preprocessing pipeline opted for in the end was Histogram Equalization followed by opening. This is the novelty of our method as the 2 techniques chosen in the end handle the illumination problem very well and also enhance the morphological features of brain tumors which will help the CNN.

D. Split the dataset into Train, Validation, and Test sets

The processed dataset has to be divided into Train and Validation datasets. The training dataset is the one on which CNN is trained while after each epoch or iteration, the learned model till that iteration can be tested on a validation set. The validation set becomes a type of test data as the model was not trained on that; thereby becoming unseen data.

Through the metrics we use on the validation dataset, we can track the progress of the model.

A 70% -30% split on the original dataset gave us the train and validation set.

Images were duplicated for a good dataset.

Test Dataset:

It has the same folder hierarchy as those of the train and validation datasets. It contains 20 images downloaded from the Internet out of which 10 contain tumors whereas 10 do not.

E. Image Augmentation

Image Augmentation is the artificial increase in the image dataset by applying specified transformations such as rotation, horizontal flipping, etc. The need for image augmentation arises when the existing dataset is not sufficient for the neural networks or if there is a scope improvement in the neural net's performance if more data is provided. Thus augmentation increases the size of the dataset. It also prevents the neural network from memorizing the data by adding some spatial variations to the images, thus preventing overfitting. The ImageDataGenerator of TensorFlow makes a generator for images that can be fed into the neural network for training and testing purposes.

The need for augmentation here is because neural networks get better when the datasets are large and since our

dataset contains 4222 images, we should increase it. We can create multiple variants of the image. Consider a cat image, if we mirror it from left to right or top to bottom, it still stays a cat. If we rotate the image, then also it stays a cat. We can create such variants manually and store them in the dataset but by doing this, we will require more memory and time.

ImageDataGenerator creates such variants internally thereby taking extremely less time and not taking a lot of memory.

Augmentation applied :

1. All images are resized to 150x150 pixels.
2. Rotation of image between -30 degree and +30 degree.
3. Horizontal shift by 20% of the image width to the left or right.
4. Vertical shift by 20% of the image height to the top or bottom.
5. Shear - Distort the image along an axis.
6. Zoom in the image by 20%
7. Apply horizontal flip to the image

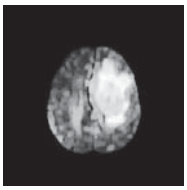


Figure 10-a: Original Image

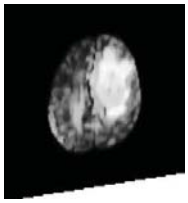


Figure 10-b: Shear

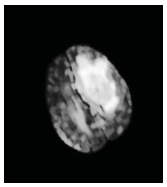


Figure 10-c: Rotation

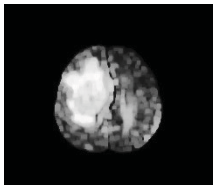


Figure 10-d: Horizontal Flip

F. Training

We used a convolutional neural network as our model as CNNs are the neural networks that are best suited for images.

Transfer learning [15] has been applied which means the training our neural network will do will be based on a pre-trained network. We have used a pre-trained model that has already learned a lot of complex features. The pre-trained model used is ResNet101v2 which will become our base model on top of which we will fine-tune our task to classify tumor and non-tumor images.

Reason for using ResNet :

In the case of normal neural networks, an increase in the number of layers will decrease the error up to a particular point but will then start increasing again. These additional layers should not hamper the training so the solution was provided in ResNet.

ResNet employs a skip connection where the output of previous layers will not only affect the next layer but also layers quite ahead of it. Using Regularization can stop the adverse effects of additional layers.

On top of the ResNet, a flatten layer was used to flatten out the matrix output of the previous layer into an array. A dense layer for further training and to avoid any case of overfitting, a Dropout layer was used. A Dropout layer drops nodes with a probability p such that any overdependence of the output on only particular nodes is avoided. The value of p used was 0.2.

The activation function used was Rectified Linear Unit (ReLU) and a sigmoid activation in the last layer as it is a binary classification-yes or no problem.

ReLU activation function outputs y=x if the input x is positive and 0 otherwise. It has gained popularity as an activation function for the non-output layers because it is easier to train and it also tackles the problem of vanishing gradients. Sigmoid activation function outputs 1/ (1+e^-x) for an input x. It outputs a probability between 0 and 1 for the input to belong to the positive class (1). Sigmoid is used in the output layer of the model and since it outputs a single value ie. the probability, there is only 1 neuron in the last layer.

The model was compiled using Adam as the optimizer with a learning rate of 0.0002 and the loss used was binary crossentropy and then the entire model was trained for 20 epochs.

G. Performance Metrics

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.

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.

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.

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.

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

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

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

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

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

Figure 11: Metrics

In the above figure:
TP - True Positive
FP - False Positive
TN - True Negative
FN - False Negative

III. RESULT

We trained our CNN model for 20 epochs and we recorded the performance metrics after the 20th epoch.

	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Training Set	97.94	98.76	98.55	98.65
Validation Set	99.33	99.45	99.73	99.59
Testing Set	95	100	90	94.74

Table 1: Metrics values

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).

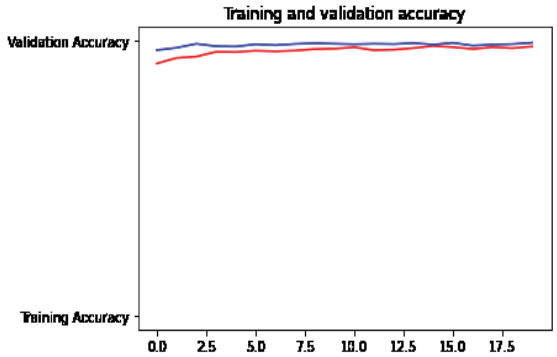

Figure 12-a: Accuracy

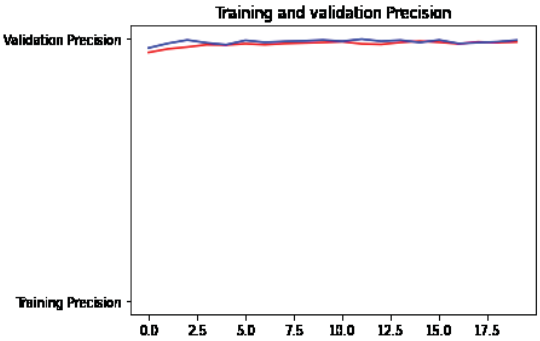

Figure 12-b: Precision

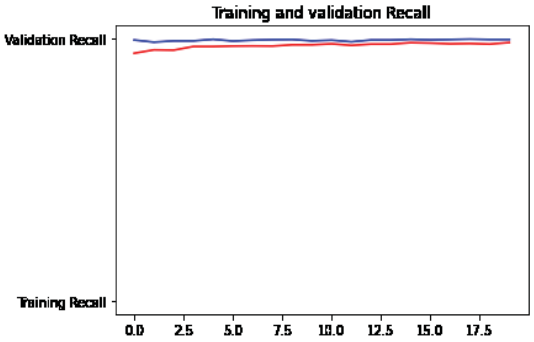

Figure 12-c: Recall

(The red line graph - Training set

The blue line graph - Validation set)

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.

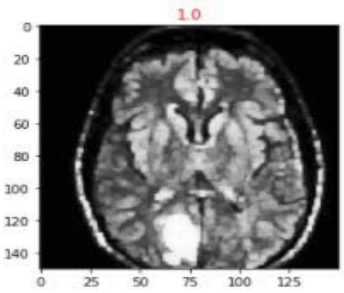

Figure 13: Wrongly Predicted Test Image

The 1.0 image title in red indicates that the image should have been classified as a tumor image (1.0) but it got classified as non-tumor (0.0). The reason for the misclassification of the above image may be attributed to the fact that the test images may not necessarily belong to the same distribution as that of the training or validation set.

Some already existing methods:

While looking at the research papers, we realized that the standard pipeline for image processing looked something like greyscaling followed by skull stripping ie. all non-brain tissues are removed using contouring or segmentation. This is followed by thresholding using histogram analysis to find out the appropriate valley region for the threshold value. The grayscale black and white image is then eroded. In some places, Berkeley wavelet transform is applied as an effective segmentation technique. This pipeline was used by Nilesh Bhaskarrao Bahadure et al. in their paper [4].

A lot of these papers used machine learning techniques that did not require as many dataset images as deep learning techniques such as CNN. Hence the experimentation in these papers was carried out using very few images.

One of the most commonly used techniques is SVM (Support Vector Machines) which uses what's known as a kernel trick to find an optimal boundary between the classes. The reason for its popularity is that it is a robust and accurate algorithm. In Arakeri et al's paper [5], the preprocessing involved rotation correction, image denoising followed by shape and texture feature extraction, and then the result was fed into an ensemble learning method that used SVM, ANN, and KNN. It was used to classify benign and malignant tumors.

Other papers to use SVM are Mariam Saii et al's paper [9], and L. Guo et al's paper [10]. In the former paper, at the preprocessing level, an anisotropic diffusion filter is applied to the image for denoising it. In the latter paper, the immune algorithm was used to search the optimal weights and parameters.

Principal Component Analysis (PCA) is also a popular algorithm that has its use in representing multivariate data tables into sets of smaller variables. This algorithm is extensively used for feature selection in a lot of research papers and this brings down the very large feature count to a reasonable one. In Sachdeva J et al's paper [6], 856 regions of interest (SROI) are extracted by the content-based active contour model. 218 intensity and texture features are extracted from these SROIs. Then PCA was used for dimensionality reduction and the result was fed into an ANN.

Deep learning techniques such as ANN (Artificial Neural Network) are also used but it is a very basic and generalized type of neural network and gets combined with other techniques such as PCA and KNN (K Nearest Neighbors) to provide good results.

The metric used was Accuracy in most of the cases and the best result was observed in D.Sridhar et al's paper who performed dimensionality reduction using DCT and then used a Probabilistic neural network (PNN) for classification. The accuracy was 100% [7].

Apart from MRI images, tumor classification has also been performed on CT scan images as seen in Padma Nanthagopal et al's paper [8]. A wavelet-based statistical texture feature set was derived from 2 level DWT. Genetic algorithm and principal component analysis were used for optimal texture feature selection. Then SVM was used for classification purposes.

Most of the research works done on this topic were on very small datasets whereas our work was done on a comparatively larger dataset giving it a better ability to generalize. Our novel method emphasizes the power of image processing – easy, simple to implement but very useful at the same time.

IV. CONCLUSION

Brain tumors especially the malignant ones are considered almost incurable and fatal. The need for early detection arises from the fact that brain tumors can have symptoms that do not seem to be alarming at first. The most common symptom of brain ailments is a headache which worsens over time in the case of brain tumors. Hence there are lots of cases where the fatality from brain tumor increased due to the diagnosis not being done early.

Brain tumor diagnosis begins with an MRI scan which is followed by studying a tissue sample for determining the type of tumor. MRI scan can also reveal additional details such as the size of the brain tumor.

This paper presents a novel method involving image processing techniques for image manipulation which would aid our CNN model to classify tumor and non-tumor images better. Image Processing techniques helped us solve the illumination issues and brought the tumor into focus. Data augmentation was used to reduce the chances of overfitting, as it artificially expands the size of a training dataset, thus bringing out an improvement in the performance and the ability of the model to generalize. Transfer learning is also used as a pre-trained model, ResNet101v2 was used as the base model, upon which further training was applied to tune our task. The system recorded an adequate accuracy of 97.94% with an excellent training recall of 98.55 % and validation recall of 99.73%.

There are limitations to our work as there are small chances that the image preprocessing applied can damage the information which makes a tumor image appear non-tumor in the eye of the CNN model. The input image should be of a good enough size because if it's not, after resizing the image to the size we have set in the image augmentation step ie. 150x150, the image can become unsuitable for use (Figure 14-a and 14-b). For future improvements, we can use ensemble techniques and combine the performance of different models for better performance.

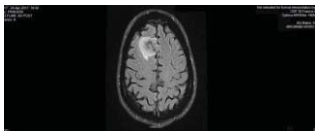

Figure 14-a: Before Resizing

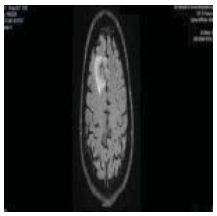

Figure 14-b: After Resizing

In conclusion, image processing proved to be effective in solving the illumination problems of the different images and reducing the noisy details thereby bringing the tumor in focus. Different variants of the images were created using image augmentation techniques which augmented the images and internally created more images for the model. CNN combined with transfer learning proved to be an effective training model which can be seen in the extremely good values of the three performance metrics.

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