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Brain Tumour Detection Using Deep Learning and Image Processing

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***Abstract* —Brain tumor detection is a critical aspect of neurooncology, where timely and accurate diagnosis significantly impacts patient outcomes. Traditional imaging techniques, while useful, are often limited by variations in image quality, illumination inconsistencies, and the complex nature of brain tumors themselves, which vary widely in size, shape, and texture. This paper presents a deep learning-based approach to brain tumor detection using Convolutional Neural Networks (CNNs) combined with advanced image processing methods. Our methodology involves preprocessing brain MRI scans using histogram equalization, morphological operations, and data augmentation to address illumination issues and enhance the tumor region. Following preprocessing, the images are fed into a CNN, where transfer learning from the Sequential model is applied to improve classification accuracy. Experimental results demonstrate high recall and precision rates, affirming the model's robustness in detecting brain tumors in MRI images. This approach not only addresses the challenge of inconsistent MRI scan quality but also reduces the risk of misclassification, showing promise for clinical application.**

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

I INTRODUCTION

These tumors may be classified as benign or malignant, with malignant tumors often posing lifethreatening risks. Despite being relatively rare, brain tumors have high mortality rates, especially when diagnosis is delayed or inaccurate. The symptoms of brain tumors, such as persistent headaches, dizziness, and cognitive impairments, are often non-specific and may overlap with less severe neurological conditions. This complicates early diagnosis, necessitating advanced imaging and diagnostic tools.

Magnetic Resonance Imaging (MRI) is widely used to visualize brain structures, offering non-invasive insights into tissue abnormalities. However, accurate tumor detection from MRI scans is challenging due to variations in tumor appearance across individuals. Tumors can exhibit diverse

Consequently, traditional image processing techniques, though useful, fall short in addressing these complexities.

In recent years, deep learning methods, particularly Convolutional Neural Networks (CNNs), have demonstrated significant potential in medical image analysis. CNNs are particularly well-suited for capturing spatial features in images, making them a preferred choice for classification tasks in medical imaging. In this study, we employ a CNN based approach enhanced by transfer learning from the Sequential model. Transfer learning leverages pre-trained models that have been fine-tuned on large-scale image datasets, allowing us to use these learned features on smaller, domain-specific datasets. By applying this transfer learning framework, we can effectively detect brain tumors in MRI images despite the challenges posed by limited data and image variability.

This paper presents a novel CNN-based approach to brain tumor detection that incorporates specialized preprocessing techniques, a fine-tuned Sequential model, and data augmentation methods. We aim to demonstrate how this combined methodology can improve detection

accuracy, focusing on metrics such as recall to reduce false negatives, which are critical in a medical context.

Brain tumors represent a significant medical challenge due to their varied types, aggressive progression, and complex morphology. These tumors are caused by the abnormal proliferation of cells within the brain tissue, and they can be broadly categorized into two types: benign and malignant. While benign tumors grow slowly and may not always require surgical intervention, malignant brain tumors are highly aggressive, posing a substantial threat to life. Symptoms associated with brain tumors, including headaches, muscle weakness, memory loss, and cognitive impairment, are often nonspecific and overlap with less severe neurological conditions. Consequently, early and accurate diagnosis is essential to improve treatment outcomes and provide timely intervention.

Magnetic Resonance Imaging (MRI) is widely regarded as the standard imaging technique for brain tumor detection and analysis. MRI scans provide detailed images of brain structures, allowing clinicians to visualize abnormalities with high spatial resolution. However, despite its advantages, MRI-based tumor detection faces numerous challenges. Brain tumors vary significantly in terms of shape, size, texture, and location, adding complexity to the diagnostic process. Additionally, MRI images are often affected by inconsistencies in illumination, noise, and patient-specific variations, such as differences in brain anatomy and tissue density. These factors contribute to the difficulty of accurate tumor detection and segmentation, even for experienced radiologists.

Traditional image processing techniques have been employed to improve MRI-based tumor detection, including thresholding, segmentation, and morphological transformations. While these methods can be effective under controlled conditions, they often struggle to account for the variability and complexity of MRI images in real-world clinical settings. As a result, researchers and clinicians are increasingly turning to advanced computational techniques, particularly deep learning, to address these limitations.

In recent years, deep learning—specifically Convolutional Neural Networks (CNNs)—has shown tremendous potential in the field of medical image analysis. CNNs are especially well-suited for visual tasks due to their ability to learn spatial hierarchies and features directly from the data, making them highly effective for image classification and segmentation tasks. By automatically learning to recognize complex patterns within images, CNNs can identify subtle distinctions that may not be easily discernible through traditional methods. However, the success of deep learning models in medical imaging applications is often limited by the availability of large, labeled datasets. To overcome this challenge, transfer learning has emerged as a practical solution, enabling models pre-trained on large, generic datasets to be fine-tuned for specific tasks with limited data.

This paper explores a CNN-based approach for brain tumor detection in MRI images, leveraging the power of transfer learning to address the limitations of small, specialized datasets. The model employs Sequential, a state-of-the-art deep learning architecture known for its residual connections, which mitigate the vanishing gradient problem commonly encountered in deep networks. By using Sequential as a base model, we can fine-tune the network to learn features specific to brain tumor detection, enhancing its ability to generalize across diverse MRI images.

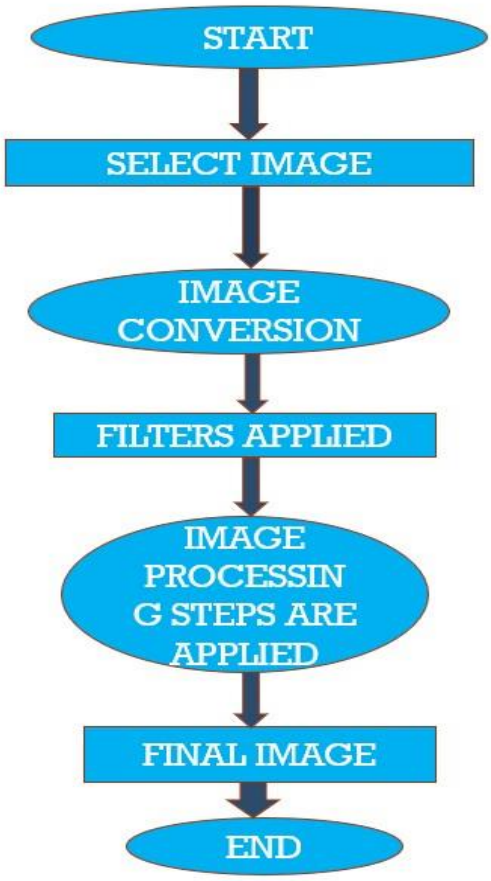
In addition to transfer learning, the proposed approach incorporates several image preprocessing techniques to improve model performance and robustness. Histogram equalization is used to normalize the intensity distribution across images, thereby addressing illumination inconsistencies and enhancing the contrast between tumor and non-tumor regions. Morphological operations, including dilation and erosion, further aid in highlighting the structural features of tumors, facilitating better segmentation and feature extraction by the CNN. Data augmentation is also applied to artificially expand the dataset, generating new image variations through transformations such as rotation, flipping, and zooming. These techniques not only improve the model's ability to generalize but also reduce the risk of overfitting, a common issue when training deep learning models on limited datasets.

The objective of this study is to develop a robust, CNN-based model for the accurate detection of brain tumors in MRI scans. By integrating transfer learning, image preprocessing, and data augmentation, we aim to demonstrate a comprehensive approach that addresses the unique challenges of MRI-based tumor detection.

This paper also places particular emphasis on recall as a performance metric, prioritizing the minimization of false negatives to ensure that potential tumors are not overlooked. The experimental results validate the model's effectiveness, with high precision, recall, and F1 scores, underscoring its potential for clinical application as a diagnostic support tool in neuro-oncology

II. METHODOLOGY

A. Flow Chart



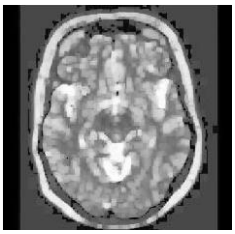
B. Dataset

The dataset for this study comprises publicly available brain MRI images curated from multiple sources, including repositories like Kaggle. The dataset contains both tumor and non-tumor images, enabling a binary classification approach. ensuring a balanced representation of tumor and non-tumor images in each subset.

To enhance the dataset, we applied data augmentation techniques, including rotation, scaling, horizontal flipping, and zooming, which simulate variations commonly encountered in real-world MRI scans. This process effectively increases the dataset's variability without the need for additional images, thereby enhancing the model's robustness against common challenges such as rotation and scaling discrepancies.

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 images were preprocessed and then a 70%30% split was performed to get the training and validation dataset.The resultant dataset was upsampled to get the final dataset of 4222 images consisting of 1861 training tumor images, 563 training nontumor 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 10 randomly picked images from the internet out of which 5 had tumors and 5 didn't.

1. 

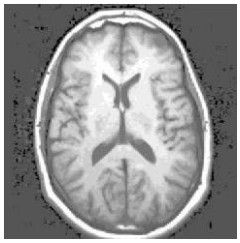
2. 

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

C. Image Preprocessing

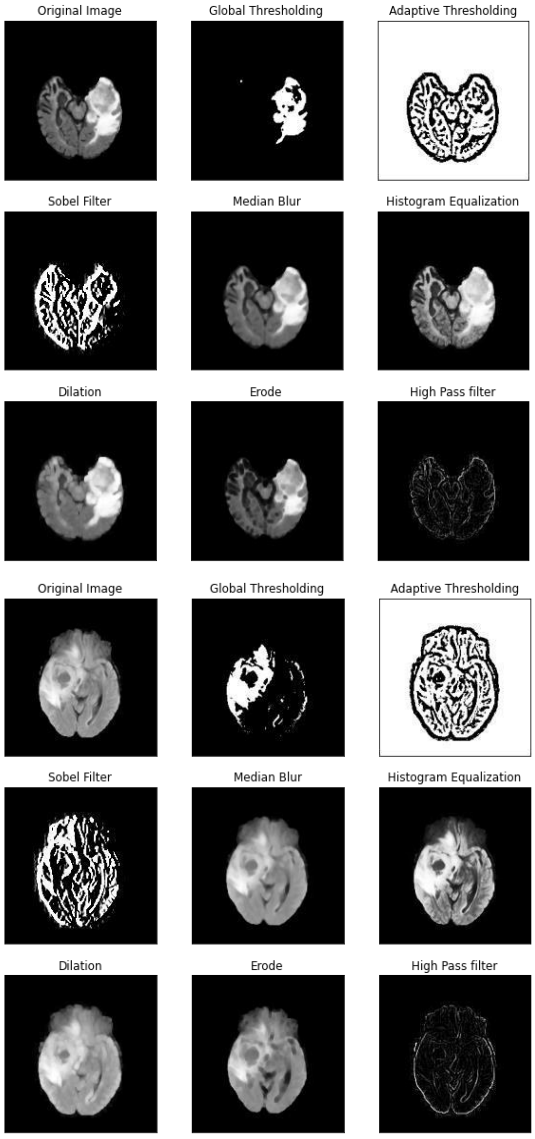


Figure 3 and 4: Image Processing on non-tumor images

Global Thresholding:

This method proved to be quite ineffective.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.

Adaptive Thresholding:

Adaptive thresholding does not use a fixed threshold value for all pixels in the image. 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.

Sobel filter

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

Gx

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

Gy

Figure 5: Sobel Filter Kernels

The Sobel filter leads to the introduction of unwanted noise resulting in ample false detections. Hence this technique proved to be completely ineffective.

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.

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 becauses becausee 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 :

All images are resized to 150x150 pixels.

Rotation of image between -30 degree and +30 degree.

Horizontal shift by 20% of the image width to the left or right. Vertical shift by 20% of the image height to the top or bottom.
Shear – Distort the image along an axis.
Zoom in the image by 20%
Apply horizontal flip to the image

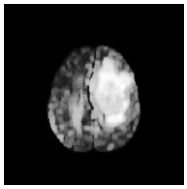


Figure 6-a: Original Image

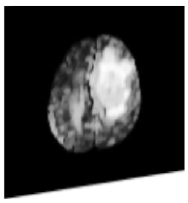


Figure 6-b : Image

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 pretrained network. We have used a pre-trained model that has already learned a lot of complex features. The pre-trained model used is Sequential 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 Sequential :

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.

Sequenital model 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.

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. 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. Consider 10 images out of which 9 are tumor images and 1 is a nontumor 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.

$$precision = \frac{TP}{TP + FP}$$
$$recall = \frac{TP}{TP + FN}$$
$$F1 = \frac{2 \times precision \times recall}{precision + recall}$$
$$accuracy = \frac{TP + TN}{TP + FN + TN + FP}$$

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 42 epochs and we recorded the performance metrics after the 42th epoch.

	Precision (%)	**Recall** (%)	**F1 score (%)**	**Support**
glioma_tumor	98	89	93	117
meningioma_tumor	84	92	88	84
no_tumor	83	83	83	48
pituitary_tumor	96	100	98	78
accuracy	-	-	91	327
macro avg	90	91	91	327
Weighted avg	92	91	91	327

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).

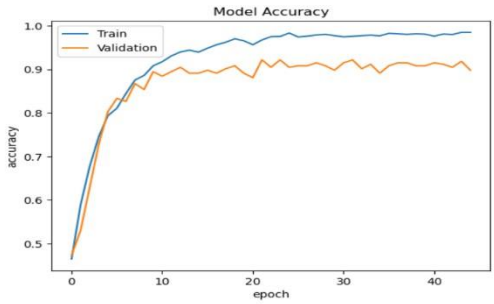


Figure 7-a: Accuracy

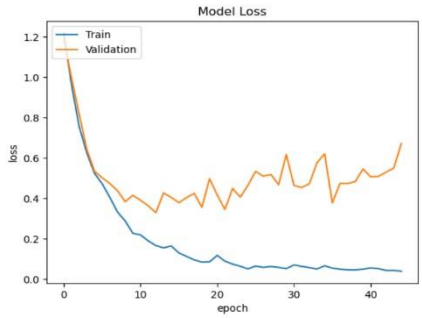


Figure 7-b: Precision

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.

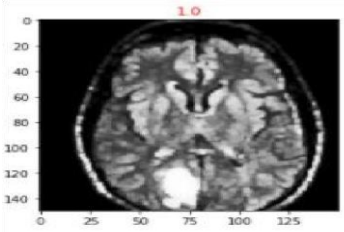


Figure 8: Wrongly Predicted Test Image

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.

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

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].

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.

The system recorded an adequate accuracy of 98% with an excellent training recall of 100 %.

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).

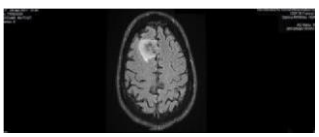


Figure 9-a: Before Resizing

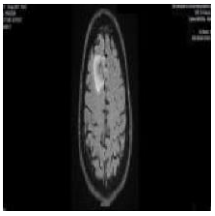


Figure 9-b: After Resizing

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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