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Efficient MRI Segmentation and Detection of Brain Tumor using CNN

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Abstract: *Intracranial tumors are a form of cancer that develops on its own inside the skull. One in every four fatalities are caused by a brain tumor. As a result, early diagnosis of the tumor is critical. A multitude of segmentation approaches is available to achieve this goal. The primary drawback of current techniques is their low segmentation accuracy. A preventative medical step of early diagnosis and assessment of a brain tumor is done with the aid of magnetic resonance imaging (MRI). Magnetic resonance imaging (MRI) provides precise information about human delicate tissue, which assists in brain tumor identification.*

Keywords: Segmentation, Brain Tumor, Convolutional Neural Network, Deep Learning, etc.

I. INTRODUCTION

Generating pictorial representations of the inside of a human being for medical assessment and to form an idea as to how the activities happen about the organs and tissues is known as clinical imaging. In order to aid the industry to diagnose and treat the diseases, clinical imaging helps undermine internal structures below the skin. It is now possible to figure out the abnormalities because clinical imaging helps develop a database of the whole anatomy. The use of a computer to modify images is referred to as "medical imaging processing." This processing encompasses a number of procedures and techniques such as picture capture, data storage, display, and transmission. The purpose of this processing is to diagnose and treat problems. This processing of images makes it easy for our algorithm to understand the data and get accurate prediction. Radiological energy, magnetic scopes, Therma, isotopic imaging, and organic imaging are all components of these processes. Several other technologies may be used to collect information on the body's location and function. When compared to techniques that generate images, such methods have several disadvantages.

Image processing is the process of changing the image properties using computational resources This method provides a number of advantages, including adaptability, data storage, and communication. Many picture scaling algorithms have been developed, allowing for effective image saving. This strategy necessitates a slew of criteria to be followed for the images to run simultaneously. Multiple dimensions can be accommodated in 2D and 3D images.

II. PROPOSED SYSTEM

In order to perform segmentation on the Tumour in an image, firstly we have to take the MRI scanned image from the chosen dataset, then pre-process the image for further enhancement, followed by using Convolutional network for successful brain tumor classification. This six-step model helps with tumour detection and locating it successfully. After the completion of all the above steps, the output is obtained. Filters like median and bilateral are used for the pre-processing whereas the Sobel filter is used for image enhancement.

III. IMAGE PREPROCESSING

Image Pre-processing is one of the most important initial steps in any CNN model. It helps in improving the image quality as well as removing any noise in the input image. The elimination of impulsive sounds and picture scaling are crucial processes in pre-processing. We start this pre-processing by first converting the Brain MRI scan images into its equivalent grey scale image.

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Unwanted noise is removed using the adaptive bilateral filtering approach, which removes distorted sounds from the brain image. This improves diagnosis while simultaneously increasing classification accuracy.

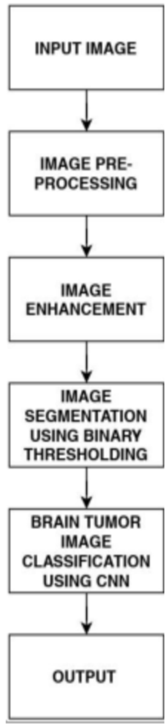

Figure 1: Block Diagram of Classification

Figure 2: Input Image for Classification Algorithm

Image Filtering: We are using the following filters to suppress the high frequencies and remove noise in the images.

Median Filter: It is a non-linear digital filtering approach commonly used to remove noise from an image or signal. Noise reduction of this sort is a popular pre-processing method used to improve the results of future processing. Because it keeps edges while lowering noise under specific conditions, median filtering is extensively used in digital image processing, and it also has applications in signal processing.

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Bilateral Filter: It is a non-linear method for blurring a photograph while retaining crisp edges. Because of its capacity to split a photograph into various sizes without causing haloes after alteration, it is commonly employed in computational photography applications such as tone mapping, style transfer, relighting, and denoising.

Using binary thresholding for Image segmentation: The method of dividing the image into compact sized elements followed by their segmentation is known as Image segmentation. Segmentation of an image helps in improving the performance of the algorithm in numerous ways. As it divides the images into small fragments, less computational power is needed and hence the accuracy of the algorithm improves. Also, it helps in removing any unwanted data which will be of no use while doing classification. This method identifies pixels based on their intensity and attributes. These portions reflect the full original image and take on properties like intensity and resemblance.

Thresholding: The most basic approach of picture segmentation is thresholding. With conversion of an image which is grayscale to a binary image with the help of labelling the various pixels present that are above or under a predetermined threshold value, the process is non-linear in nature.
We utilise the cv2.threshold() method in Open CV: cv2.threshold(src, thresh, maxval, type[dst])
A single-channel array is subjected to fixed-level thresholding using this function. The function is commonly used to extract a bi-level (binary) picture from a grayscale image for filtering each of the pixels which are either subsequently quite large or are significantly quite small.

Morphological Operations: Morphological approaches are also employed in conjunction with multiple methods of segmentation. Normally, these operations are conducted on binary pictures. Residing on shape possibilities, it carries out multiple image processing methods. The pair of morphological processes to be used among others in our proposed work are erosion and dilation and the treatment using this pair is done at once.

IV. BRAIN TUMOUR IMAGE CLASSIFICATION USING CNN

The probability of a convolutional network determining the spatial and temporal relationships in an image is high when appropriate filters are used. The proposed method complements a superior fitting to the whole dataset, because of the multiple parameters and reusable weights. Training the network is feasible to enhance the recognition of the sophistication of the image. A convolutional network helps in compressing the images into formats that aren't difficult to process without risking the loss of components that are necessary for the creation of a satisfactory prediction. In this phase, we have to make use of Keras as well as the other packages that we'll be using to create the CNN.

1. **Sequential:** To begin the neural network, we build a Sequential class object.
2. **Convolution:** Convolution2D is used to create the image-processing convolutional network.
3. **Pooling:** The Pooling layer is responsible for reducing the spatial size of the convolved feature. Dimensionality reduction reduces the amount of computer power required to process the data. Average and maximum pooling are the two types of pooling. Average pooling helps in retrieving the average of all the values from the area of the images under the kernel. Max pooling on the other hand retrieves the maximum value under the areas covered by the kernel. In general, we employ maximum pooling. We decrease the size of the feature map in this stage.
4. **Flattening:** For their use in the subsequent surface at this very step, every pooled feature map is to be combined within a single vector. To flatten every such feature map, the flatten function is used.
5. **Fully Connection:** The next step is to use Keras' dense function to feed the vector we acquired earlier into the Neural Network. Output is the initial parameter denoting all the concealed layer nodes. The output layer is the next to be added. Because we're anticipating a binary conclusion, we'll utilise the sigmoid activation function in this situation.

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V. BRAIN TUMOUR IMAGE SEGMENTATION

After successfully classifying whether the image has a brain tumor or not, we move to the segmentation part. Segmentation is implemented using a Convolutional Neural Network algorithm with a custom loss function. It has 19 hidden layers and is based on Unet architecture. Our algorithm segments tumors with high accuracy of 91%.

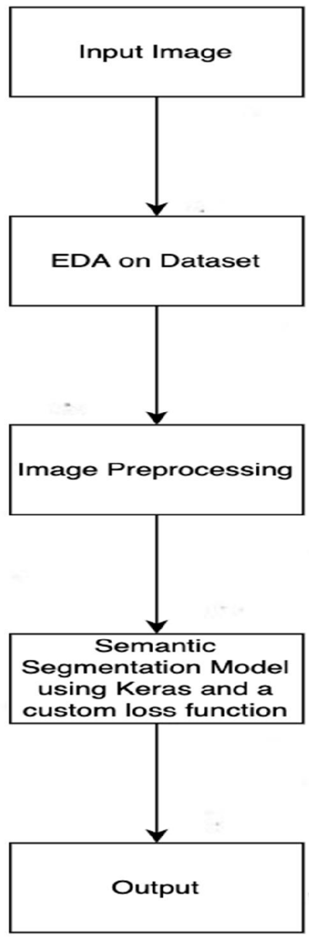

Figure 3: Block Diagram of Segmentation

VI. EXPERIMENTAL RESULTS

To get the best accuracy, we have tried different combinations of epochs value as well as batch size and found the best combination which gives us the best accuracy.

Epochs	Batch Size	Accuracy
10	16	98.33%
12	20	96%
16	5	91%

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VII. PERFORMANCE MEASURE

After undergoing multiple performance tests, the evaluation suggests the approach of true positive and true negative. These approaches help specify the number of times a damaged area is well identified as a damaged area and when the non-damaged area is identified as a non-damaged area.

False-positive is the phenomenon when the method is not able to precisely detect the damaged part whereas false negative is the phenomenon in which the algorithm fails to correctly determine the undamaged areas.

Algorithm	Epochs	Batch Size	Accuracy
Classification	10	16	97%
Segmentation	50	32	91%

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

$$Specificity = \frac{TN}{TN + FP}$$

$$Sensitivity = \frac{TN}{TP+FN}$$

For classification algorithm we got an accuracy of 98% and for segmentation part we got a accuracy of 91% which is quite good for medical applications.

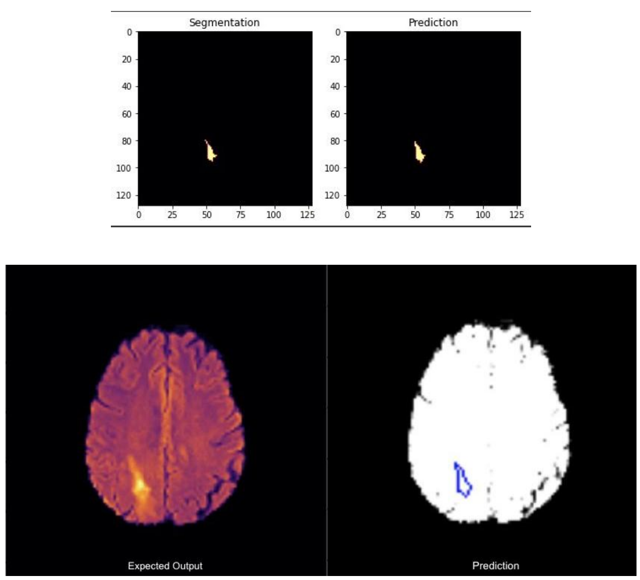

Figure 4: Comparison Between Expected and Predicted Output

VIII. DICE COEFFICIENT

The task of every pixel being assigned a label is known as semantic segmentation Here, various objects of the same class are treated as a single entity. For completing the tasks like object detection, scene understanding, scene parsing, etc, the field of semantic segmentation for pre-processing is considered to be of high value.

One of the essential metrics used for semantic segmentation is the Dice Coefficient (F1 score). The dice coefficient can be determined by the division of area overlapped*2 and the total number of pixels in both the images.

IX. CONCLUSION

Making use of the Convolution Neural Network, we've proposed a method for efficient classification and segmentation of brain tumors. Reading the file path on the local device, the input MR images are read and then transformed into grayscale images. In order to eliminate the noises that came along with the previous image, we made use of the Adaptive Bilateral Filtering technique. Finding out the portions of the brain where the tumor resides is done after applying binary thresholding to the denoised image which is run through the convolutional neural network which helps do the segmentation. Without any errors and with exceptionally less computational time, our model shows an accuracy of 91%.

X. FUTURE SCOPE

Extermination reveals that the suggested technique requires a more powerful algorithm and more cleaned data. Also, the accuracy can be improved by using a more diverse dataset. But as we know in medical field it's really difficult to acquire data and in certain circumstances it's not even possible. Hence considering all this, the suggested method must be strong enough to recognize tumor areas from scanned datasets. This approach can be enhanced further by partnering with less robustly trained algorithms that can detect anomalies with less cleansed training data, as well as self-learning algorithms, which would aid in enhancing the algorithm's accuracy and decreasing processing time.

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