Brain Tumor Detection Using Deep Learning

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Abstract - Identifying brain tumors and improving patient care are the goals of this project. Brain malignant tumors, which are aberrant cell growths, are known as tumors.

Frequently infectious brain tissues are caught by CT and MRI scans. There are many other methods that are used for the detection of brain tumors and some of them are positive charges imaging and cerebral X-ray photography of blood or lymph vessels and tests at the molecular level. So, this paper will use different MRI images to detect aliment cause like tumors.

The main purpose of this research paper is to 1) identify irregular sample images and 2) find the tumor area.

The abnormal sections of images will forecast the levels of tumors so that proper treatment can be done. Deep learning is used to find abnormal regions from sample images. This paper will use VGG-16 to segment the abnormal part. The density of the infected region is defined by the number of pixels with malignancy.

Keywords— Medical Images, Brain tumor, MRI, Deep Machine Learning, CNN, Keras.

I. INTRODUCTION

Our body is made up of different types of cells and tissues. Similarly, our brain which is the most significant and special organ of our body, is made up of special kinds of tissues. The unknown growth or increase in masses of tissues lead to abnormalities in that body part which is the tumor. While these abnormalities develop in our brain part leads to immense pain. But advancements in modern technologies have made its cure a piece of cake. Now its cure can be done without opening that body part with the help of image processing.

"Intracranial neoplasm" is the term that is used to define brain tumors. Tumors can be of the dangerous type and benign type. Standard MRI images distinguish the tumors on the basis of their different textures and different change in graphical qualities. 120 distinct types of dangerous brain tumors are categorized by the World Health Organization (WHO) [1]. Depending on the damaged region of the brain, each type of brain tumor has a unique set of symptoms. Different indications of brain tumors are pain in the head, temporary confusion, vision less, nausea, different disorders in the mind, amnesia and loss of balance, etc [2].

There are many reasons like age, exposure at different places, different radiations and electromagnetic waves from different modern technologies, infections, etc, for the development of such abnormalities in our body parts [3]. There are only two types of tumors that can cause cancer, first one is that develop in the brain part while the second one is that develop in other body parts and then spread to the brain.

Brain tumor risk factors include ionizing radiation, vinyl chloride exposure, neurofibromatosis, and other variables. During treatment, focal neurological deficits such as motor deficits, aphasia, or visual field defects are possible. TTP and known sizes of tumors can help in better prevention of side effects of brain tumors [4].

An approach that trains computers how to react to any situation similar to any human reaction is called deep learning. Using deep learning, a computer model is able to classify images, sounds, and text. It has been demonstrated that occasionally, deep learning algorithms outperform humans. Human-made neural networks have many running neural networks that are popular. Each node is connected to the others and all these nodes together form neurons at different parts of the body [5]. The main idea of this research is to find brain tumors through sample MRI images by developing a CNN-based system. To determine the efficacy of the suggested categorization approach, it was put to the test and compared to currently employed classification techniques.
II. RELATED WORKS

The most important part of developing a Neural Machine learning system is to develop image segmentation and its classification which is very much common in diagnosis. Mircea Gurbin, Mihaela Lascu, and Dan Lascu et al. [6] introduced a method that uses techniques like CWT, and DWT and make use of supervised algorithms like SVM. Different layers of wavelets are trained that ultimately helps to find the distinct types of brain tumors due to which it takes a lot of time. (Tumor), normal tissues (White Matter (WM) and Gray Matter (GM)) and fluid. Somasundaram S. and Gopinath R. et al. [7] explore the different image processing techniques for tumor detection, especially for deep processing which suggests the 3D sample images. Damodaran S. and Raghavan D. et al.[8] presented an NN-based method where they used 10 images with tumors and another 10 without tumors. (Cerebrospinal Fluid (CSF)), extraction of the relevant features from each segmented tissues and classification of the tumor images with Neural Network (NN).

Figure 2: Depicts the proposed system's system architecture, acquiring of images, preprocessing, division of images, property extraction, and classification are the components.

L. Sujihelen and M. Janardhan et al. [9] proposed a data mining system that uses an automatic image processing technique which makes it very fast and efficient. Dr. Babu Anton P. and Reema Mathew A. et al.[10] stated that the exact location and size of tumors can be detected with some calculations. These calculations are done by hand so, it is very time taking. Xiaoja Wang, Xianying Qi and Rui Wang et al.[11] presented an ideal technique that uses the properties of segmented MRI images. Classification of images on the basis of their super high quality, division on the basis of their properties, etc were used in this method.

III. PROPOSED METHOD

A. Image Acquisition

Numerous biomedical imaging records are accessible for the purpose of brain tumor identification research. Common techniques include magnetic resonance imaging (MRI) and computed tomography (CT). Other techniques include positron emission tomography, cerebral angiograms, lumbar punctures, and molecular testing for the diagnosis of brain tumors. Nonetheless, they are costly. The water molecules, waves, etc inside our body present the whole picture of our body through MRI. To circumvent the complexities of conventional scanning procedures, portable and small MRI equipment are now being developed. MRI delivers a higher level of detail and information. Here, the MRI dataset provided to Kaggle by Navoneel Chakrabarty has been used [12]. It contains 155 abnormal images and 98 normal brain images. In this dataset, "yes" corresponds to photographs of tumors, and "no" corresponds to images of healthy tissue. Here, the augmentation procedure is also employed to expand the sample size. Maximum rotation up to 10 degrees, the maximum change in width up to 0.1, maximum change in width up to 0.1, change in brightness from 0.3 to 1.0, and horizontal and vertical flips. From the total, 2530 images of an enhanced dataset are selected. The final collection consists of 1550 abnormal photographs and 980 regular ones.

B. Pre-processing

The purpose of preprocessing is to prepare the brain images for further processing [13]. This technique is mostly reliant on the data collection equipment, which possesses its own inherent characteristics. If the supplied data is 3D, conversion to grey scale or 2D is necessary. To minimize noise in biological images, median filtering is most effective. The collection contains images of varying
resolutions. Image is processed as a standard rotation and size is given to images.

The image quality is improved via histogram equalization. The photos are improved using a contrast-constrained adaptive histogram equalization technique.

C. Image Segmentation

The sample is divided into several parts as a process of improvement. This phase is essential for feature extraction since it involves separating a specific picture region from its backdrop. The elementary phases of segment illness consist of thresholding and morphological procedures (erosion, dilation, opening). However, at this level, it is difficult to find the abnormalities in specific regions. The intensity of the healthy photos mimics that of the tumor area. Thus, the segmentation procedure can be utilized to separate the brain from the skull. Within this Region of Interest (ROI) is the tumor. A thresholding approach based on OTSU yields a segmented mask of the skull [14].

The active contour approach outlines the region's perimeter. Additionally, the second stage of segmentation can be applied to the ROI to generate the tumor region mask. This approach may not provide satisfactory outcomes with healthy photographs. This segmented picture may be used to examine the characteristics of the tumor area, which will aid in the assessment of density.

D. Feature Extraction

The behavior or symptom of the sickness can be exemplified by computing the disease's actual characteristics.

The choice of characteristics has a significant impact on classification. Frequent traits [15] include asymmetry, diameter, and uneven border.

E. Classification

For the purpose of diagnosing disorders based on brain images, several machine-learning approaches are employed. Artificial neural networks may be used to categorize [16] if the characteristics are retrieved in a certain sequence. A neural network classifier assumes that each attribute is independent of the others. In this scenario, the categorization of tumor images using deep learning algorithms will succeed without segmentation. Deep neural networks may be constructed using convolutional neural network techniques [17].

Figure 6 depicts the general architecture of convolutional neural networks. Deep learning automatically extracts the feature from the full image. CNN model performs this operation. An increase in the thickness of CONV layers leads to more feature mapping. The proper time to start the model is when the dimension is very less. Layers are pooled down to sample the feature dimension. Layers that are fully connected can change each label's score. SoftMax layers use feature and class scores to prepare the model.

For the purpose of using the images of brain tumors as training, the CNN architecture's dimension is somewhat altered. In Table 1, the changed model system is noted.
**Figure 6:** Common architecture of CNN

\[ f(x) = \frac{1}{n\sigma\sqrt{2\pi}} \sum_{i=0}^{n} e^{-\frac{1}{2} \left( \frac{x_i - \mu}{\sigma} \right)^2} \]  

\[ \ldots \ldots \ldots \ldots \ldots \ldots \ldots (2) \]

**IV. TABLE AND FIGURES**

| Model: 'BrainTumorDetectionModel' |
|-----------------------------------|
| Layer  | (type) | Output Shape | Param # |
|-------|--------|--------------|---------|
| Input_1 (InputLayer)             | (None, 240, 240, 3) | 0 |
| zero_padding2d (ZeroPadding2)    | (None, 244, 244, 3) | 0 |
| conv0 (Conv2)                    | (None, 238, 238, 32) | 4736 |
| bn0 (BatchNormalization)         | (None, 238, 238, 32) | 128 |
| relu0 (Activation)               | (None, 238, 238, 32) | 0 |
| max_pool0 (MaxPooling2)          | (None, 59, 59, 32) | 0 |
| max_pool1 (MaxPooling2)          | (None, 14, 14, 32) | 0 |
| flatten (Flatten)                | (None, 6272) | 0 |
| fc (Dense)                       | (None, 1) | 6273 |

Total params: 11,137
Trainable params: 11,073
Non-trainable params: 64

**Table 1: Altered Model Architecture**

Karas uses the binary cross entropy loss and Adam optimizer for constructing models. The default rate of learning is 0.001. The model is designed with a batch size of 32 across 24 epochs. Our trained model provides an accuracy of 95.5 percent for the sample images. Using a mix of multilayer thresholding, morphological techniques, and contour extraction, the tumor location is located in pictures that have been recognized as having brain tumors.

where \( T \) is the average of the image's intensities from highest to lowest. To divide the regions into sections, utilize the morphological open function. All of the regions' contours are shown, and the tumor region is located in the region with the largest area. The Gaussian kernel distribution can be used to estimate the tumor area's density.

**V. RESULT**

![Results of tumor detection: (a) input image (b) Abnormality Detection (c) Tumor region detection (d) tumor mask for density estimation](image)

Figure 8: Results of tumor detection: (a) input image (b) Abnormality Detection (c) Tumor region detection (d) tumor mask for density estimation

The suggested system's goal is to categories malignant brain tumors from MRI scans. Kaggle dataset had 253 MRI pictures. For simulating a deep neural network, the number of data points is insufficient. As a result, 2530 photos were produced using the augmentation technique. Following cropping, the extracted images are resized to (240, 240) resolution. The model is built using the Karas framework (with Tensor Flow as the backend). To examine the system's performance, two different forms of segmentation are
used at various levels. Both before and after classification, segmentation was performed. Segmentation comes after classification, according to the performance analysis, and produces superior results. When used with typical MRI pictures, this technique runs more quickly. If abnormal images are found, segmentation is the next process that is taken. The sensitivity and specificity relationship can be seen in the ROC curve.

Thus, the best methods for the dataset are multilevel thresholding and OTSU thresholding. A convolutional Neural Network with improved methodology enabled 98% accuracy in the result. The use of the Gaussian kernel distribution in the density estimation approach is also suggested.

A web interface can be added to this system to make it more functional. Different diseases can also be found through this model. Other properties other than density may also be estimated for clinical purposes.

VI. CONCLUSION

This research presents a novel deep learning approach for brain tumor detection. Early cancer identification is important for prompt and efficient treatment. For research purposes, the Kaggle dataset contains MRI scans of high quality. A variety of segmentation algorithms were tested.

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