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Brain Disease Classification using Convolution Neural Network

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Abstract: *The diagnosis of brain tumours demands extreme precision since even the smallest errors in judgment can have serious consequences. Because of this, segmenting brain tumours is a significant medical difficulty. There are now a number of tumour segmentation methods, however none of them are very accurate. Here, we offer a machine learning-based approach to segmenting brain tumours. The numerous approaches, including image processing, picture capture, pre-processing, segmentation, feature extraction, and classification, are presented in detail in this study. In this study, we looked at various brain MR pictures and segmented each one to determine if it was benign or cancerous using Convolution Neural Network methods.*

Keywords: Segmentation, Tumor, Machine Learning, MR images, Convolution Neural Network

I. INTRODUCTION

Uneven tissue growth is typically referred to as a tumour in medicine. A brain tumour is an uneven mass of tissue where the regular cell control mechanisms do not appear to be able to stop the uncontrollable growth of the cells. Depending on whether they are cancerous or not, brain tumours can either be malignant or benign. Anatomical images can be obtained using the imaging technique known as magnetic resonance imaging (MRI). Magnetic resonance principles are used by MRI scanners to produce an image of our internal organs.MRI scans are used by medical practitioners to identify a range of illnesses, from cancers to torn ligaments. We can determine the aberrant cells present in our brain tissues from these high-resolution photos. Unlike an X-ray, an MRI shows all necessary detail clearly and without radiation. It is a flexible procedure since imaging techniques allow for adjustment of the contrast between different tissues.

For instance, it is possible to create images with strong contrast by adjusting the gradient pulses. There are many techniques used nowadays to classify an MRI picture, including variation segmentation, neural networks, and fuzzy algorithms. Numerous techniques have been developed for medical image processing that make it possible to automate classification tasks quickly and accurately. The steps of feature extraction, feature selection, image segmentation, and image classification are crucial in the processing of medical images. In order to achieve low computation time and good accuracy, feature selection is even more crucial than feature extraction. The majority of techniques for classifying brain tumours rely entirely on segmentation. As a result, the issue of classification and feature extraction, which is not only the most crucial phase but may also help to increase CAD performance, is only given a little attention.

The diagnosis of numerous serious diseases, including lung cancer and the image analysis of breast cancer, currently yields the greatest results when these procedures are integrated with image processing techniques. Though machine learning approaches were found to be helpful, the demand for greater accuracy and real-time processing recently compelled users to explore a new subject called deep learning because of its improved models.

II. LITERATURE SURVEY

Menze BH, Jakab A,Bauer S, Kalpathy-Cramer J, Farahani K, Kirby J,et al.., "The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS)," outlined the methodology and findings of the Multimodal Brain Tumor Image Segmentation Benchmark (BRATS). A set of 65 multi-contrast MR scans of patients with low- and high-grade gliomas that were manually annotated by up to four raters and 65 comparable scans produced using tumor image modeling software were subjected to 20 cutting-edge tumor segmentation algorithms.

L. Wang, F. Shi, G. Li, W. Lin, J. H. Gilmore and D. Shen, "Patch-driven neonatal brain MRI segmentation with sparse representation and level sets," utilizing sparse representation methods, a novel patch-driven level sets method for segmenting neonatal brain pictures has been developed. We specifically use sparse representation in a patch-based manner to create a subject-specific atlas from a collection of aligned, manually divided photos.

L. Wang, Y. Gao, F. Shi, G. Li, J. Gilmore, W. Lin, et al., "LINKS: learning-based multi-source Integration framework for Segmentation of infant brain images," utilized the random forest method to successfully combine features from many sources of pictures for tissue segmentation. Initially, just the multi-modality (T1, T2, and FA) pictures were included in the multi-source images; later, the tissue probability maps for the cerebrospinal fluid, white matter, and grey matter were added.

C. Li, R. Huang, Z. Ding, J. C. Gatenby, D. N. Metaxas and J. C. Gore, "A Level Set Method for Image Segmentation in the Presence of Intensity In homogeneities With Application to MRI," a brand-new region-based approach to picture segmentation that can handle intensity in homogeneities is proposed. We first derive a local intensity clustering property of the image intensities based on the model of pictures with intensity in homogeneities and define a local clustering criterion function for the image intensities in a neighbourhood of each point.

III. PROPOSED METHODOLOGY

The methodology of proposed system, we describe a Convolution Neural Network-based method for automatically segmenting brain tumors'. Our project's key contribution is the classification of the tumor's type based on the MRI scan images we were able to obtain. The dataset we are dealing with has only ever been the subject of classification of tumor types. This dataset has been the subject of past research, none of which is intended for segmentation. Compared to the current systems, the accuracy was significantly increased utilizing this strategy. By using this strategy, we can get high levels of confidence.

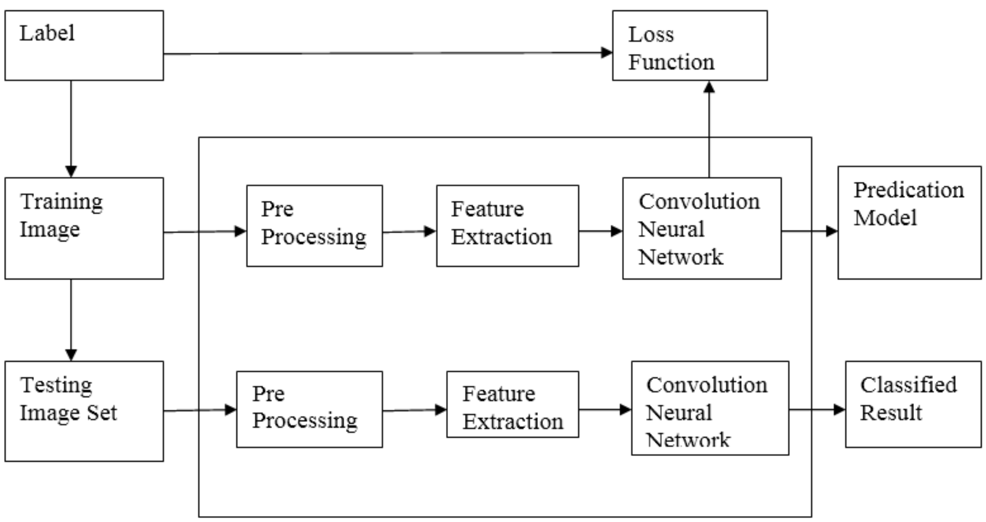

Figure 1: Block diagram

3.1 Pre-processing

Data pre-processing is the most crucial stage of a machine learning project, notably in computational biology, and a crucial step in the data mining process. It will be more challenging to make discoveries during the training phase if there is more noisy and unreliable data, irrelevant and recurrent information, or both. Therefore, we preprocess the provided MRI image. The tasks involved in data preparation and filtering can take along time to process. Cleaning, instance selection, normalization, transformation, feature extraction and selection, etc. are all examples of data pre-processing. The final training set is the end result of the data pre-processing.

3.2 Blurring

When minute features need to be removed from a picture before object extraction or when there are small gaps in lines or curves, blurring is utilized in the preprocessing processes. The goal of this method is to replace each pixel's value in a picture with the average of the grayscale values in the area specified by the filter mask.

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3.3 Adaptive Histogram Equalization

A computer image processing method called histogram equalization is used to enhance contrast in photographs. This is achieved by successfully extending the intensity range of the image and spreading out the most common intensity levels. Usually, using this technique, photos' overall contrast is increased. In contrast to conventional histogram equalization, adaptive histogram equalization redistributes the image's brightness values by computing multiple histograms, each of which corresponds to a different region of the image.

3.4 CLAHE

The contrast limiting of Contrast Limited AHE (CLAHE) sets it apart from adaptive histogram equalization. For CLAHE, the contrast limiting process is used on each neighborhood that serves as the source of a transformation function. CLAHE was created to stop the excessive noise amplification that adaptive histogram equalization might cause. In order to lessen the issue of noise amplification, Contrast Limited AHE (CLAHE), a form of adaptive histogram equalization, limits the contrast amplification. Before calculating the CDF, CLAHE clips the histogram at a predetermined value to reduce the amplification. As a result, the transformation function's transformation function's slope is constrained. The so-called clip limit, or value at which the histogram is clipped, is a function of the histogram's normalization and, consequently, of the size of the neighborhood region.

3.5 CNN

Convolution neural networks (CNNs, or ConvNets) are a form of deep, feed-forward artificial neural networks used in machine learning that have been effectively used to analyze visual data. Comparatively speaking to other image classification algorithms, CNNs employ a minimal amount of pre-processing. This implies that the filters, which were manually designed for traditional techniques, are learned by the network. This feature design's independence from prior knowledge and human effort is a significant benefit.

3.6 Classification

Data must often be divided into training and taste sets in classification tasks. Each instance in the training set has a number of attributes as well as a goal value (the class labels) (i.e. the features).

IV. ALGORITHM

Step 1: The various folders include images
Step 2: The identified folders are used to build a CNN model.
Step 3: To create the CNN model, there are many, many layers of relu layer.
Step 4: To strengthen the model, 2D convolution, max pooling, white spreading, and flattening are used.
Step 5: We can forecast the class of the predicted image by feeding input images into an existing model.

V. RESULTS

1. Image Input Window: In this window we are going input for our project.

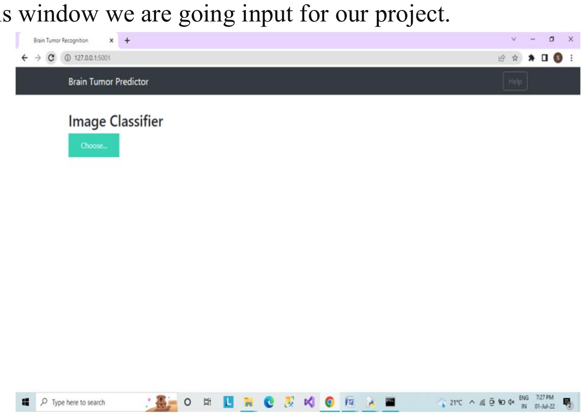

Figure2: input window

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2. To train the project : To train the project, the images are train using convolution neural network model .

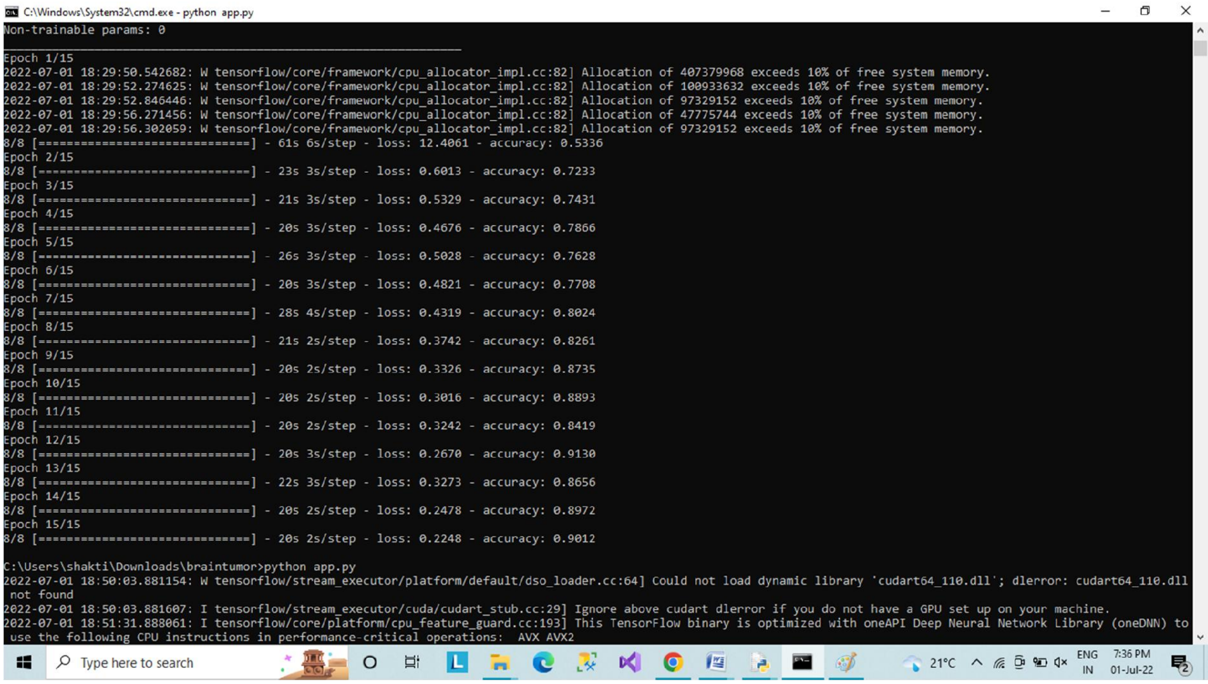

Figure2: Train data

3. To choose an input image : before we have take an image, first train the images and after training we have to choose the image.

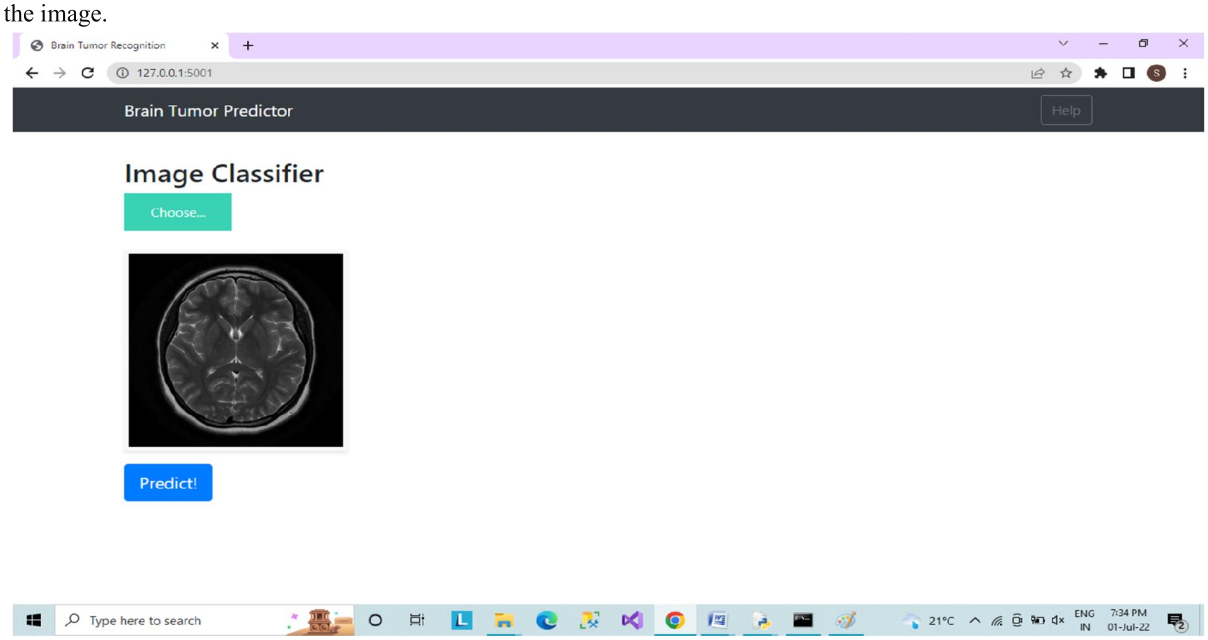

Figure 3: choose an image

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4. The Result: The output

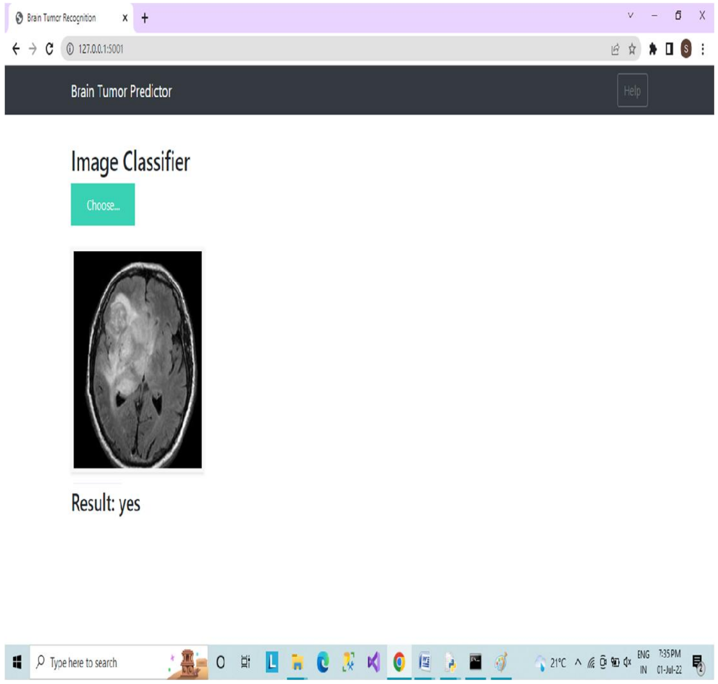

Figure 4: In this image the tumor is present it will show a result yes.

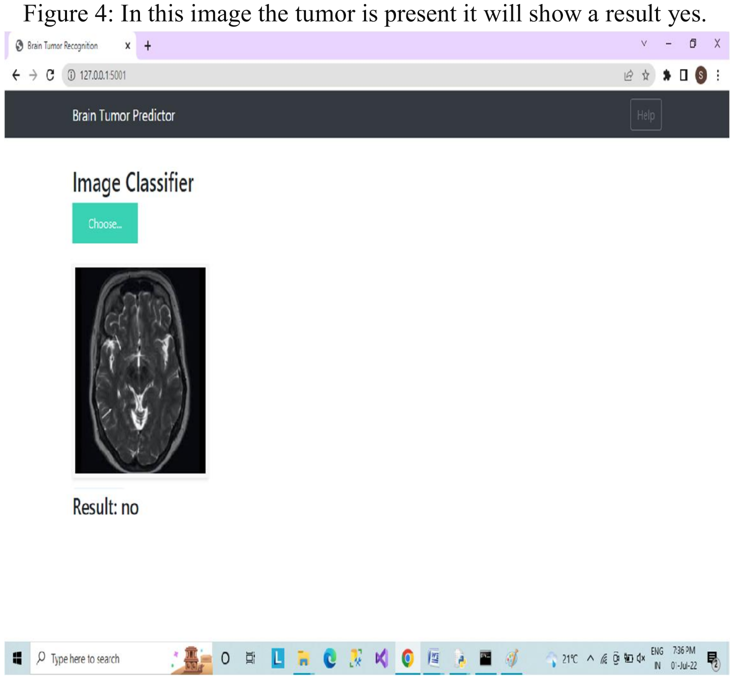

Figure 5: In this image the tumor is not present it will shown a result no.

VI. CONCLUSION

The use of machine learning models for the detection of brain tumors was covered in this project. To segment MRI scan pictures that were provided as input, we employed a CNN pre-trained model that was selected based on a number of factors. The end result indicated whether or not the given MRI brain scan contained cancerous tumors' (malignant) or not (benign).

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REFERENCES

[1]. Menze BH, Jakab A,Bauer S, Kalpathy-Cramer J, Farahani K, Kirby J, et al., "The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS)," Medical Imaging, IEEE Transactions on, vol. 34, pp. 1993-2024, Dec 4 2015.

[2]. M. Prastawa, E. Bullitt, S. Ho, and G. Gerig, "A brain tumor segmentation framework based on outlier detection," Med Image Anal., vol. 8, pp. 275-283, 2004.

[3]. S. Bauer, L.-P. Nolte, and M. Reyes, "Fully automatic segmentation of brain tumor images using support vector machine classification in combination with hierarchical conditional random field regularization," MICCAI, vol. 6893, pp. 354-361, 2011.

[4]. Nicholas J. Tustison, K. L. Shrinidhi, MaxWintermark, Christopher R. Durst, Benjamin M. Kandel, James C. Gee*, et al.*, "Optimal Symmetric Multimodal Templates and Concatenated Random Forests for Supervised Brain Tumor Segmentation (Simplified) with ANTsR," Neuroinformatics, vol. 13, pp. 209-25, Apr 2015.

[5]. L. Wang, F. Shi, G. Li, W. Lin, J. H. Gilmore and D. Shen, "Patch-driven neonatal brain MRI segmentation with sparse representation and level sets," 2013 IEEE 10th International Symposium on Biomedical Imaging, San Francisco, CA, USA, 2013, pp. 1090-1093, doi: 10.1109/ISBI.2013.6556668.

[6]. C. Li, R. Huang, Z. Ding, J. C. Gatenby, D. N. Metaxas and J. C. Gore, "A Level Set Method for Image Segmentation in the Presence of Intensity In homogeneities With Application to MRI," in IEEE Transactions on Image Processing, vol. 20, no.7, pp. 2007-2016, July 2011, doi: 10.1109/TIP.2011.2146190.