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Brain Tumor Classification Using CNN

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ABSTRACT

Brain tumours are dangerous and serious disorders affected by uncontrolled cell growth in the brain. Brain tumours are one of the most challenging diseases to cure among the different ailments encountered in medical study. Early classification of brain tumours from magnetic resonance imaging (MRI) plays an important role in the diagnosis of such diseases. There are many diagnostic imaging methods used to identify tumours in the brain. MRI is commonly used for such tasks because of its unmatched image quality. The traditional method of identifying tumours relies on physicians, which is time-consuming and prone to errors, putting the patient's life in jeopardy. Identifying the classes of brain tumours is difficult due to the high anatomical and spatial diversity of the brain tumour's surrounding region. An automated and precise diagnosis approach is required to treat this severe disease effectively. The relevance of artificial intelligence (AI) in the form of deep learning (DL) has revolutionized new methods of automated medical image diagnosis. As a result, good planning can protect a person's life that has a brain tumour. Using the 2D Convolutional Neural Network (CNN) technique, this project proposes Computer-Aided Diagnosis (CAD) a deep learning-based intelligent brain tumour detection framework for brain tumour type (glioma, meningioma, and pituitary) and stages (benign or malignant).CNN is used to classify tumours into pituitary, glioma, and meningioma. Then it classifies the three grades of classified disease type, i.e., Grade-two, Grade-three, and Grade-four. The performance of the CNN models is evaluated using performance metrics such as accuracy, sensitivity, precision, specificity and F1-score.From the experimental results, our proposed CNN model based on the Xception architecture using ADAM optimizer is better than the other three proposed models. The Xception model achieved accuracy, sensitivity, precision specificity, and F1-score values of 99.67%, 99.68%, 99.68%, 99.66%, and 99.68% on the MRI-large dataset. The proposed method is superior to the existing literature, indicating that it can be used to quickly and accurately classify brain tumours.

Keywords: Brain tumor, MRI, Classification, Tumor grade.

I. INTRODUCTION

There are many types of brain tumours. Each type can differ in growth rate, typical location, size at the time of diagnosis, and who they affect. Brain tumours are the most common type of tumour in children, and the second or third most common type in young adults (breast cancer is highest in females). Some brain tumour types affect males more often than females, or vice versa. The following are a few of the more common brain tumours and the percentage of the tumour count among all brain and other central nervous system (CNS) tumours[1].

Meningioma (38%) arises from the membranous covering of the brain (meninges). Most are benign and grow slowly inward from the meninges to push on the brain and surrounding structures.

Glioma (25%) arises from glial cells that surround and support the neurons of the CNS. Tumours in this category are further classified according to the type of glial cell from which they originate (astrocytoma, glioblastomamultiforme, ependymoma, oligodendroglioma, mixed glioma). Although some types are relatively benign, gliomas comprise 80% of malignant brain or other CNS tumours.

Pituitary tumour (17%) arises from the pituitary gland at the base of the brain. The pituitary gland is important for normal hormone release. Most pituitary tumours are benign. However, large tumours can compress nearby nerves and tissues, causing vision defects and hormone abnormalities[2].

1.1 Grades of Tumour

Normally, the severity of cancer is assessed using a staging system that's broken into 4 or 5 stages depending on the size and development of the tumour. Brain cancers, however, are assessed using a system of grades, with the 'grade' of a tumour denoting how aggressively it grows. Higher grade tumours tend to grow faster, have an aggressive course, and are more likely to be malignant[3].

Grade I – The tumour is benign. The cells look nearly like normal brain cells. This grade is the least aggressive.

Grade II – The tumour is malignant. The cells look more abnormal, but they are generally slow-growing cells.

Grade III – This is a malignant tumour with cells that look very abnormal and are actively growing (anaplastic).

Grade IV – The malignant tissue has cells that look most abnormal and tend to grow quickly[4].

II. PROBLEM STATEMENT

The main goal behind the development of our proposed model is to automatically distinguish people with brain tumors, while reducing the time required for classification and improving accuracy. A novel and robust DL framework CNN has been proposed for detecting brain tumors using MRI datasets. The proposed model is a four step process, in which the steps are named: 1) Pre-processing, 2) Feature Extraction, 3) Feature Reduction, 4)Classification. Median filter, being one of the best algorithms, is used for the removal of noise such as salt and pepper, and unwanted components such as scalp and skull, in the pre-processing step. During this stage, the images are converted from grey scale to coloured images for further processing. In second step, it uses Grey Level Co-occurrence Matrix (GLCM) technique to extract different features from the images. In third stage, Color Moments (CMs) are used to reduce the number of features and get an optimal set of characteristics. Images with the optimal set of features are passed to CNN classifiers for the classification of Brain Tumor Type and their grades[5].

Region Proposal Network

This region proposal network takes convolution feature map that is generated by the backbone layer as input and outputs the anchors generated by sliding window convolution applied on the input feature map[6].

GLCM Feature Extraction

Grey Level Co-occurrence Matrix (GLCM) based texture analysis of kidney diseases for parametric variations. The investigations were carried out using three Pyoderma variants (Boil, Carbuncle, and Impetigo Contagions) using GLCM. GLCM parameters (Energy, Correlation, Contrast, and Homogeneity) were extracted for each colour component of the images taken for the investigation. Contrast, correlation, energy, and homogeneity represent the coarseness, linear dependency, textural uniformity, and pixel distribution of the texture, respectively. The analysis of the GLCM parameters and their histograms showed that the said textural features are disease dependent. The approach may be used for the identification of CKD diseases with satisfactory accuracy by employing a suitable deep learning algorithm[7].

Convolutional Layer: In the convolutional layer, a filter (known as a kernel) is used to determine the existence of patterns in the input images (original image), after which several filters can be employed to extract different features. The filter is a small size to have the ability to scan the whole image and apply the appropriate arithmetic between the filter and the pixels to extract the features. The filter settings are reset during the periodic training phase, and when the network has been trained for a retinacula number of epochs (epochs imply all training samples have been entered simultaneously), these filters start looking for different characteristics in the image. Simple and evident features, such as edges in various directions, are extracted using the first hidden layers. The complexity of the attributes which must be recognized and extracted rises as we go deeper into the network's hidden levels[8].

Pooling Layer: The purpose of the pooling is to reduce the size of the activation maps. This is not necessary but prevents you from falling into an overfitting situation. The idea behind clustering is simple, as large arrays are scaled down[9].

Fully-connected Layer: This layer is the last, where neurons are fully connected to all nodes of the previous layer. The final classification process takes place in it.

To design the network model, first, an image is inserted into a convolutional layer, and an activation function is applied to the output of the convolutional layer, such as ReLu. The function's output is sent to another convolutional layer; the process is repeated several times, sending the output to an assembly layer. The steps are repeated several times, and trainable classifiers are produced. The output is also sent to the fully convolutional layer, which has the probability of each class want to train the network on. In the input layer, the range can be from 0 to 1. Each neuron is treated as a filter where the filter is computed for the data network depth; in the convolutional layer, the neurons are filters in image processing to detect edges, curves, etc. Each filter of the convolutional layer will have its image features, such as vertical edges, horizontal edges, colors, textures, and density.

All neurons add to the feature extractor array for the entire image. In addition, the pooling layer is sandwiched between successive convolutional layers to compress the amount of data and parameters and reduce overfitting. In short, if the input is an image, then the main function of the pooling layer is to compress the image by resizing the image. When the information removed when the image is compressed is just some irrelevant information

III. SYSTEM ANALYSIS

Dataset Preparation and Exploration

Configuring and training the algorithms

Before starting the training process, the algorithms (DCNN) usedin this paper have to be configured to segment brain tumor. DCNN and SSDhave separate configuration files which have been provided by TensorFlow Brain Tumor Detection API. The following configuration has been made to DCNN andSSD algorithms to be able to segmenttumor present in an MRI Brain Image.

Dataset splitting: The dataset used in this split is split in such a way that80% of the images are used for training the algorithms while the remaining 20%is used for testing.

Number of classes: Classes here is nothing but the number of segments that DCNN and SSD should learn and detect after training. In this case, thealgorithms are responsible to detect 7 class.

Learning Rate: Default learning rate of 0.0002 has been used to train the algorithms.

Label Map: A label map tells the trainer and algorithms what each object is inan image, by mapping the class names to class id numbers.

Batch Size: Batch size refers to the number of training samples which can beused by the algorithm in one iteration.

Pre-processing

Brain Tumor Image pre-processing are the steps taken to format images before they are used by model training and inference.

The steps to be taken are:

1.Read image

2.Grey Scale conversion

3.Resize image - All the images collected are modified to be less than 200KB in size with a maximum resolution of 1280 times 720 because the larger the images are the longer it will take to train the algorithms.

Original size (360, 480, 3) — (width, height, no. RGB channels)Resized (220, 220, 3)

4.Remove noise (Denoise) - smooth our image to remove unwanted noise. This is done using gaussianblur[11].

Binarization

Image binarization is the process of taking a grayscale image and converting it to black-and-white, essentially reducing the information contained within the image from 256 shades of grey to 2: black and white, a binary image.

Feature Extraction

Medical images contain tumours characterized by different locations and different types of pathologies, shape, size, density, as well as the size of the area of the affected tissue near the tumour space. For generating images and classifying the pixels in each image, need to extract the features of original images. In the proposed networks, the construction of the feature extraction part which combines a bottom-up pathway and a top-down pathway. The key of generating images and segmenting images depends on the feature representation. There exit two tasks in this approach: generating segmentation images and discriminating the class of each pixel in each image[12].

IV. RESULT

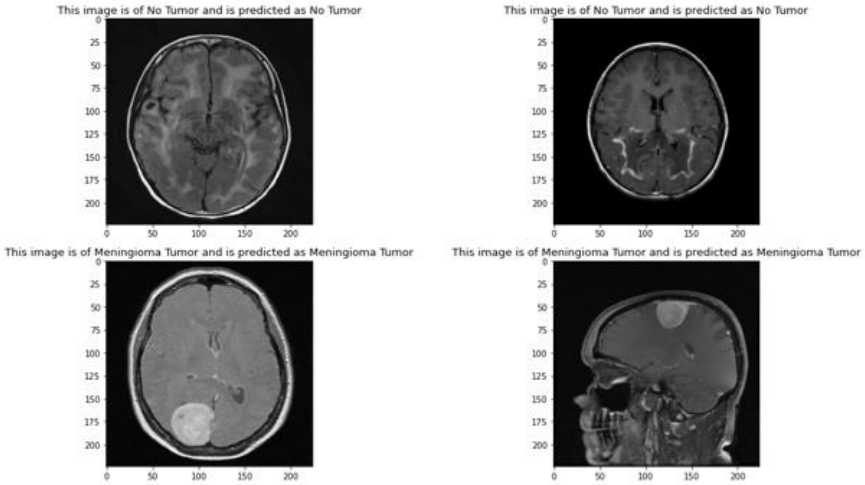

Figure :1

V. DIAGRAM

1. DATA FLOW DIAGRAM

A data flow diagram (DFD) maps out the flow of information for any process or system. It uses defined symbols like rectangles, circles and arrows, plus short text labels, to show data inputs, outputs, storage points and the routes between each destination.

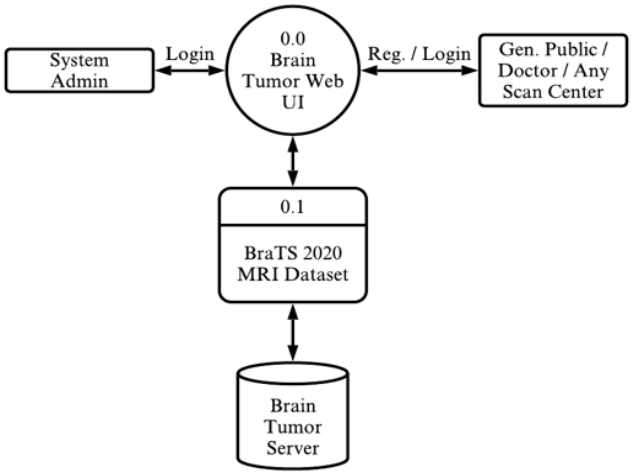

Figure :2

2. CLASS DIAGRAM

The class diagram is defined as the property of the objects in the given class, function and the attributes. Also the class diagram is used to find the flow and execution of the project.

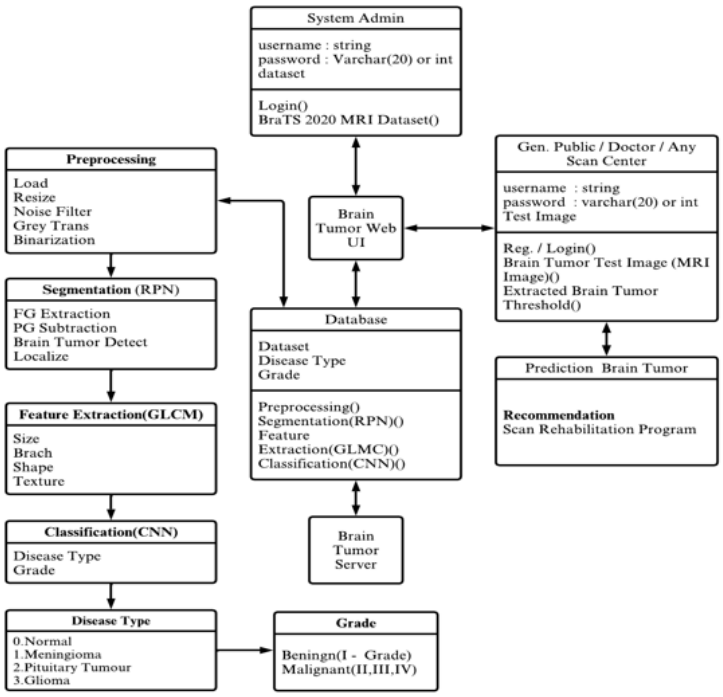

Figure :3

VI. CONCLUSION

The latest developments in medical imaging tools have facilitated health workers. Medical informatics research has the best options make good use of these exponentially growing volumes of data. Early detection options are essential for effective treatment of brain tumors.This project presented a CAD approach for detecting and categorizing BT's radiological images into three kinds (pituitary-tumor, glioma-tumor, and meningioma-tumor).Also, classified glioma-tumor into various categories (Grade-two, Grade-three, and Grade-four) utilizing the DCNN approach (i.e.,proposed work). Firstly, pre-trained DensNet201 deep learning model was used, and the features were extracted from various DensNet blocks. Then, these features were concatenated and passed to softmax classifier to classify the brain tumor. Secondly, the features from different Inception modules were extracted from pre-trained Inceptionv3 model and concatenated and then, passed to the softmaxfor the classification of brain tumors.The proposed method produced 99.51% testing accuracy on testing samples and achieved the highest performance in detection of brain tumor.The outcome of the presented architecture

shows high training and validation accuracy with low training and validation loss. Moreover, the testing phase determines the overall portable EM imaging system's capability and potential of CNN architecture in detecting and localizing the brain tumor with high accuracy.

VII. FUTURE ENHANCEMENT

In summary, future enhancements for In the future, going to increase MRI images in the used dataset to improve the accuracy of the proposed model. Moreover, Applying the proposed approach to other types of medical images such as x-ray, computed tomography (CT),Positron Emission tomography(PET) and ultrasound may constitute a principle of future studies.

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