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Brain Glioma Detection and Grading using 3D MRI Scan

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ABSTRACT

The most prevalent condition affecting the brain, spinal cord, and central nervous system is brain tumors. Brain tumors are difficult to detect using medical imaging because they vary in size, form, and location depending on the patient. Therefore, precise knowledge of a tumor's shape, size, and location is necessary for its identification by medical imaging. The segmentation and grading of brain gliomas using a 3D magnetic resonance imaging (MRI) scan is done in this project using Python Jupyter software and Convolutional Neural Network (CNN) architecture. The entering picture data must first be transformed before being processed further using techniques like subset division and data visualization. Before entering data, all of these stages must be completed for the CNN deep learning model to function. The initial stage of pre-learning was converting the collection of brain tumor images into a format that could be read by a Python machine. The subset division step was used to divide the dataset because of the created Numpy arrays' size and resource limitations. Next, the dataset's patterns are made evident through the use of data visualization. An autonomous system is built to handle the glioma segmentation task in pre-operative MRI scans using a CNN-based deep learning model. The CNN deep learning technique is used to do pixel label segmentation on the tumor area. Accurately segmenting a brain tumor into smaller pieces provides more information about the tumor's condition. This algorithm has also attained excellent accuracy and performance. This efficiency indicator can be used for assessing the segmented tumor region's performance. Predicting the final image is the last stage.

Keywords: Brain Glioma, CNN, Segmentation, MRI, Data Visualization.

1.INTRODUCTION

The most common primary brain tumor, gliomas develop quickly and cause devastating neurological effects. The most frequent brain tumors are called gliomas. Based on their level of aggression, the World Health Organization (WHO) divides them into four classifications. According to conventional classification, diffuse gliomas can be classified as low-grade or high-grade (HGG, WHO grade III and IV) [1]. The prognosis is closely linked to tumor grade, therefore the ability to categorize non-invasively is important for clinical planning and decision-making. This served as the inspiration for our work, which classified LGG/HGG utilizing MRIs and non-invasive diagnostic methods [2].

In recent years, there has been a substantial advancement in our understanding of the molecular ethology of gliomas in children and adults. These developments will supplement the histology-based categorization with better diagnostics and mutational profile-based classification schemes. Additionally, a better knowledge of the molecular ethology of these tumors has led to the discovery of novel molecular targets and the defining of treatment approaches that may soon provide better results. Currently, the degree of tumor resection, patient age, and general and neurological function status are still considered traditional prognostic variables that impact prognosis [3, 4].

Thus, automatic tumor segmentation is favored, particularly for big data sets and situations requiring ongoing tumor surveillance and flexible treatment scheduling [5]. However, because tumor sites, forms, and structures vary widely, reliable automatic tumor segmentation is typically difficult. Pathology examination-based tumor grading necessitates biopsies, making it an invasive and time-consuming method that is susceptible to inter-observer variability and erroneous sampling [6, 7]. For clinical use, automatic tumor segmentation and grading derived immediately from MRI would therefore be very advantageous.

This study prescribes that the data be transformed before handling incoming image data further, employing methods including subset division and data visualization. Data transformation is used to convert the brain Glioma image dataset into a Python computer-readable format. The subset division step was used to divide the dataset because of the created Numpy arrays' size and resource limitations. The segmentation and grading of brain gliomas using a 3D MRI scan are done in this project using Python Jupyter software and CNN architecture.

2. RECENT WORKS

Several methods exist for automatic MRI-based tumor segmentation, primarily based on generative or discriminative models [8]. Atlas-based models, among other generative models, rely on prior anatomy information and classify voxels using posterior probabilities, then segment tumors using image registration.

Human 3D image collections are studied in the multidisciplinary field of medical image processing. Clinicians diagnose human diseases; radiologists carry out this task. Effective diagnosis of brain illnesses is possible thanks to MRI pictures, which show the internal anatomy of the brain in precise detail [9]. It is located in the brain but also aids in the diagnosis of illnesses in other human body regions, such as the spinal cord. X-rays, CT scans, ultrasounds, and mammograms are additional medical imaging modalities in addition to MRIs that are used to diagnose a variety of disorders in other human body parts. Fast processors assist translate the visuals to energy, which are subsequently converted to signals [10, 11]. These signals signify the many bodily tissues that are present. The images may be handled by the computer through the use of Medical Image Processing techniques [12].

The application of medical image processing is widespread. It seeks to highlight many facets of crucial topics: the fundamental procedures such image creation, image processing, and image administration. Data collection and the processes involved in reconstructing the images make up image formation [15]. Image computing is used to increase interpretability. Getting the right information is helpful. Compression, storage and retrieving, and communication with the imaging data were all handled by image management.

3. PROPOSED SYSTEM

This study suggests using CNN architecture to separate and grade different brain states associated with brain diseases. The incoming image dataset is first sent through a data transformation process that transforms it into a Python Numpy array format for brain tumor images. To reduce the size of the generated Numpy array, a subset division step is applied. Subsequently, the process of data visualization is employed to effectively illustrate the patterns present in the dataset. Tumors vary widely in size, location, and shape, and this may be precisely determined with the CNN segmentation technique. Creating the output image is the last stage.

This is the Classifier that is suggested in Figure 1.

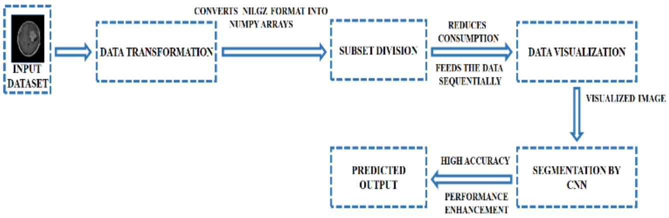

Figure 1: Proposed CNN Classifier

The supplied image dataset is first subjected to the data transformation procedure. The brain tumor image collection is transformed using this method into a Python Numpy array format. The produced Numpy array was large, so large RAM was required for extra pre-processing and training. Subset division is therefore applied. Given the size and resource constraints of the created dataset, a subset division step is used to divide it. The technique of data visualization, which is utilized to make the patterns in the datasets easily visible, comes next for the datasets. CNN segmentation based on deep learning techniques handles the segmentation stage for this modulus after data visualization. Tumors vary widely in size, location, and shape, and this may be precisely determined with the CNN segmentation technique. In this last output stage, the CNN classification also offers good specificity and sensitivity for identifying images with or without tumors. Creating the output image is the last stage. All things considered, the suggested work was created in Python using the Jupyter program.

A. Data Transformation

The preprocessing stage is dedicated to precisely eliminating the redundancy that exists in the captured image while maintaining the nuances that are essential to the overall process. It is carried out to enhance an image's visual appeal and qualities. Following morphological activity, a region filling operation is performed to remove holes from the input image in an attempt to remove small objects and noise from the background. Preprocessing is typically measurable or quantifiable. Preparing raw data for further data processing involves various types of processing, one of which is called data preprocessing. This may entail selecting meaningful ranges to concentrate on, combining important variables when it makes sense, or arranging unstructured data. It has always been a crucial first stage in the data mining procedure. It involves tasks like grouping salient variables together when it makes sense, organizing unstructured data, and determining crucial focus ranges.

The basic goal of data transformation is to take data from a source, transform it into a format that can be used, and then send the transformed data to the system that is intended to receive it. During the extraction phase, data is typically in its unusable raw original form since it is being pulled into a central repository from various sources or locations. The extracted data must be changed into the intended format by going through a number of steps in order to guarantee its usability. A raw data source is usually transformed into a format that has been cleaned, verified, and is ready for use.

Extract/transform/load (ETL) is another term for the data transformation process. The extraction step consists of locating and eliminating data from the various source systems that generate it, then transporting the data to a single repository. The initial info is then cleansed if needed. This is followed by a conversion into a target format suitable for usage in analytics software. Data type conversion, duplicate data removal, and source data enrichment are possible transformations.

B. Subset Division

Given the size and resource constraints of the created dataset, the subset division step was used to divide it. Due to the size of the generated Numpy array, extensive RAM availability was needed for additional pre-processing and training. Thus, this module is used to feed the data progressively and minimize RAM usage. Furthermore, by eliminating extraneous elements from the input image, category brain slicing and narrow object areas reduced the size of the images. A watershed method was used to complete basic picture segmentation. Feature scaling was then used to normalize each individual feature, concluding the pre-learning process.

C. Data Visualization

Data visualization is the act of converting information into a visually appealing environment, such as a map or graph, so that people can understand it and draw conclusions from it. Data visualization is the branch of data analysis that deals with how data is shown visually. It is an effective tool for presenting conclusions derived from data since it presents data graphically. It is impossible to examine all of our data, much less manually process and understand it, due to large data collections. Data visualization comes in quite handy here to portray vast and tiny data sets. Both tiny and huge data sets can be represented effectively with the help of data visualization. The field of data analysis that deals with the visual display of data is called data visualization.

D. Segmentation by CNN

In digital image processing and analysis, segmentation is a widely used technique that divides a picture into many portions or sections, usually according to the properties of the image's pixels. Image segmentation divides an image into a collection of regions with lots of pixels, each of which can be represented by a mask or a labeled image. Comparing distinct regions of an image is another often used technique. Among other ways, this strategy is applied in the region expanding, clustering, and thresholding approaches. Many more approaches to picture segmentation have been developed over time, making use of domain-specific knowledge to effectively handle segmentation problems in certain application fields. So let's start with CNN segmentation, which is one of the clustering-based techniques for segmenting images.

CNN offers a segmentation-free approach that does away with the requirement for labor-intensive, hand-crafted feature extraction methods. As a result, various researchers have put forth various CNN architectures. Numerous image data points were included in the multiclass brain tumour detection reported by the majority of CNN models. A CNN is a comprehensive learning method designed for image identification and categorization. CNN is employed in numerous practical contexts. The biological neural networks utilized in image processing, speech recognition, and other applications are the same as CNNs. CNNs may be trained to recognize objects in photos, classify images, and reliably predict the next word in a pattern.

Rather of manually evaluating the MRI pictures, a CNN-based algorithm will assist medical practitioners in their therapeutic role to speed up the recovery process. CNN is used in face recognition, image classification, and other computer vision applications. It bears similarities to the basic neural network. CNN has learnable parameters, such weights and biases, just as neural networks. Despite their resource and skill difficulty, CNNs offer comprehensive findings.

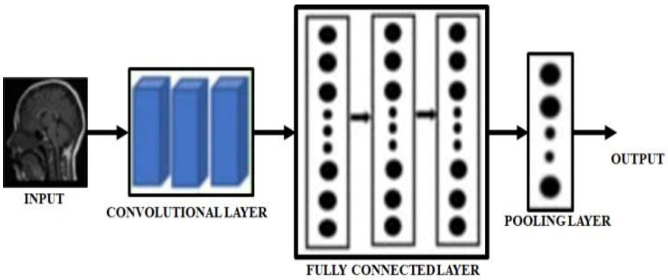

Figure 2: CNN architecture diagram

As the CNN architecture diagram in Figure 2 shows, there are several CNN levels. The process of separating and identifying an image's distinctive characteristics so that a convolution tool can be used for analysis is known as feature extraction. Fully connected layer that determines the class of the image using previously extracted data using the convolutional process' output.

3.1 CNN Algorithm

CNN Classification

Convolution kernel startup.

Convolution layer output evaluation.

$$C_{out}=f\left(\sum_{j=0}^{J-1}\sum_{i=0}^{I-1} y_{m+i,n+j}\, w_{ij}+b\right) \qquad (3.1)$$

Where,

y - Filtered input of M*N matrix;

w - Convolution kernel of J*I matrix;

b - Bias=1; f- activation function (ReLu).

ReLu layer will apply an element wise activation function.

$$f(y)=\max(0,y) \qquad (3.2)$$

It ranges from 0 to infinity.

Pooling layer

Reduces the number of parameters to learn.

Compute dimensions of cout using pooling layer. For this method max pooling layer is taken. It takes the largest element from the rectified feature map.

$$p=(n_h-f+1)/s*(n_w-f+1)/(s*n_c) \qquad (3.3)$$

Where,

n_h - Height of feature map,

n_w - Width of feature map,

n_c - Number of channels in the feature map,

f - Size of filter

s - Stride length

Fully Connected Layer

Dropout layer reduce over-fitting on neural networks

n- Output of neuron, if chosen no. is less than n then output will be dropped.

Determine output of fully connected (dense) layer.

$$F_j^l = f\left(\sum_{i=1}^{n} p_i^{l-1} w_{ij}^l + b^l\right) \quad (3.4)$$

Where,

l - Current layer

w_{ij} - Connection weights

4. RESULTS AND DISCUSSION

This section uses an image dataset to assess the suggested method. CNN is used to segment the provided dataset after it has been assessed by Python software. The output provides an effective image prediction.

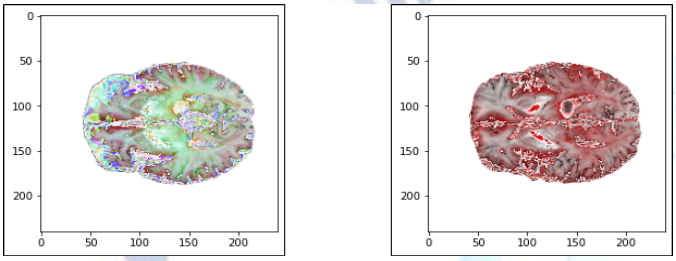

Figure 3: A single arrangement comprising of 4 separate sequences.

Figure 3 shows that the brain dataset is four separate sequences in a single arrangement.

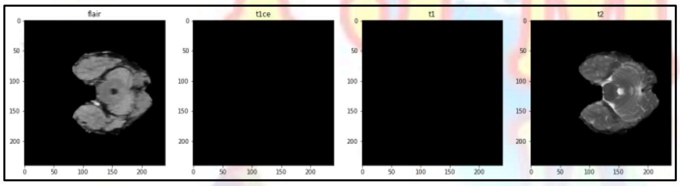

Figure 4: Visualized images of the different sequences (Depth)

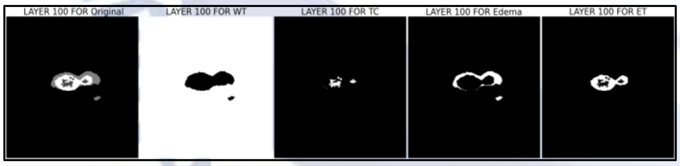

Figure 5: Visualized images of the brain mask segmentation (Layer)

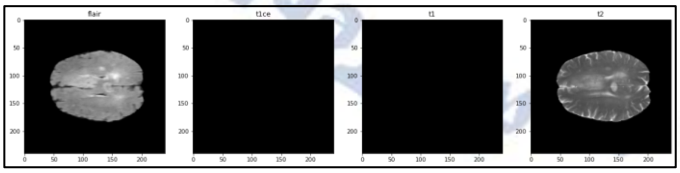

Figure 6: Visualized images of the different sequences (Layer)

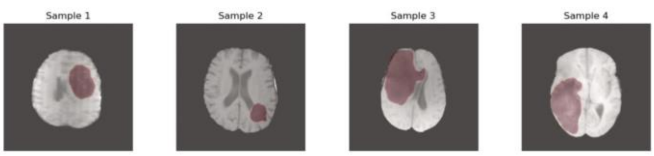

Figure 7: Predicted images for after segmentation

The various depth-based sequences' well-defined pictures are displayed in Figure 4. Sequencing depth has a significant impact on the reliability of variation detection; the more aligned sequence reads there are at a given place, the more confidently a base is called.

The brain mask segmentation based on layer is shown in Figure 5, where the images are well-represented. Brain mask datasets are sets of pictures or information with a particular function in mind: brain mask segmentation. Brain mask segmentation is the process of locating and defining the brain region.

Figure 6 shows various layer-based sequences with well-represented images. These data demonstrated excellent agreement between the Flair imaging T1-weighted sequence, which was used because of patient motion, and traditional T1-weighted imaging.

Figure 7 displays the sample images for the post-segmentation brain tumor prediction. The results of image segmentation are either a set of contours that are extracted from the image or a set of segments that together encompass the entire image.

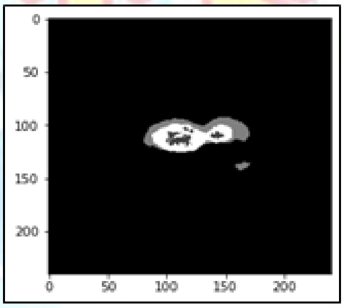

Figure 8: Brain Mask Segmented Image

Every weight in every layer of CNN is learnable. CNN it was created expressly to perform semantic segmentation and pixel classification on medical pictures, much like these. The segmentation of the brain mask using the CNN architecture is shown in Figure 8.

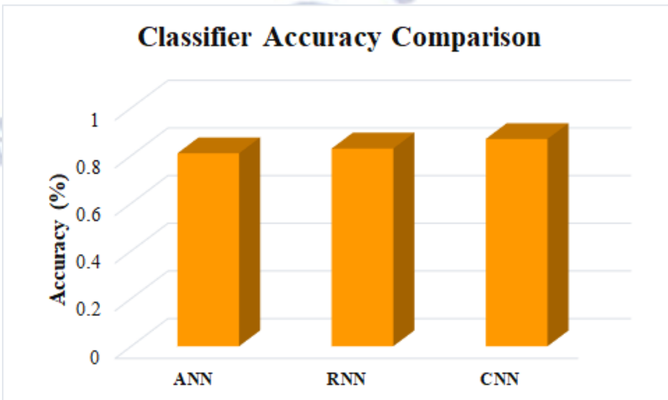

Figure 9: Classifier Accuracy Comparison

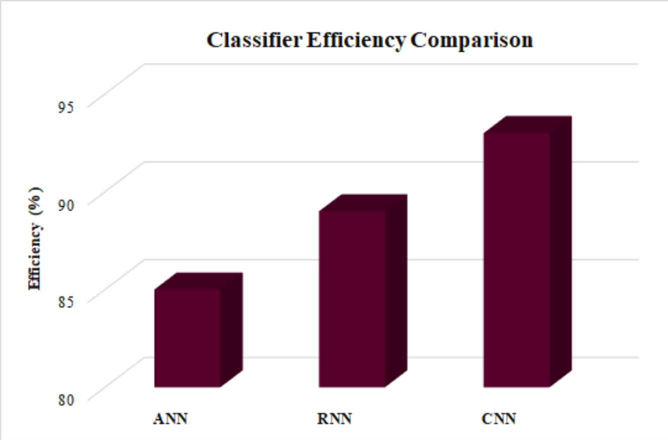

Figure 10: Classifier Efficiency Comparison

Figures 9 and 10 compare the accuracy and efficiency of the controller. It demonstrates that the suggested CNN is more accurate and efficient, and as a result, segmentation produces an accurate output that is capable of accurately predicting tumour cells.

5. CONCLUSION

The proposed methods include automated multimodal brain tumor segmentation and deep learning-based state grading of brain Glioma. The goal of this study is to categorize and detect early diseases more precisely and effectively. The Python Jupyter software, which expertly handled the Python programming language, carried out all of this job. In this work, the Brats 2019 dataset is used. The first step in the pre-learning process involved converting the collection of brain tumor images into a format that could be read by a Python machine. The subset division step was used to divide the dataset because of the created Numpy arrays' size and resource limitations. Subsequently, the dataset's patterns are made evident through the data visualization process. Moreover, the brain image segmentation process makes advantage of CNN architecture. This illustrates the efficacy of the project and the possible application of CNN for fast tumor segmentation, and the accuracy and overall performance are assessed.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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