

Brain Tumor Detection using Deep Learning and Convolution Neural Network Algorithm

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Abstract: Now a day's tumor is second leading cause of cancer. Due to cancer large no of patients are in danger. The medical field needs fast, automated, efficient, and reliable technique to detect tumor like brain tumor. Detection plays a very important role in treatment. If proper detection of tumor is possible then doctors keep a patient out of danger. Various image processing techniques are used in this application. Using this application doctors provide proper treatment and save a number of tumor patients. A tumor is nothing but excess cells growing in an uncontrolled manner. Brain tumor cells grow in a way that they eventually take up all the nutrients meant for the healthy cells and tissues, which results in brain failure. Currently, doctors locate the position and the area of brain tumor by looking at the MRI Images of the brain of the patient manually. This results in inaccurate detection of the tumor and is considered very time consuming. A tumor is a mass of tissue it grows out of control. We can use a Deep Learning architectures CNN (Convolution Neural Network) generally known as NN (Neural Network) and VGG 16(visual geometry group) Transfer learning for detecting the brain tumor. The performance of the model is predict image tumor is present or not in image. If the tumor is present, it returns YES otherwise return NO.

Keywords: CNN, Deep learning, Brain tumor.

1. Introduction

The human body is made up of many organs and brain is the most critical and vital organ of them all. One of the common reasons for dysfunction of brain is brain tumor. A tumor is nothing but excess cells growing in an uncontrolled manner. Brain tumor cells grow in a way that they eventually take up all the nutrients meant for the healthy cells and tissues, which results in brain failure. Currently, doctors locate the position and the area of brain tumor by looking at the MR Images of the brain of the patient manually. This results in inaccurate detection of the tumor and is considered very time consuming.

A Brain Cancer is very critical disease which causes deaths of many individuals. The brain tumor detection and classification system is available so that it can be diagnosed at early stages. Cancer classification is the most challenging tasks in clinical diagnosis.

This project deals with such a system, which uses computer, based procedures to detect tumor blocks and classify the type of tumor using Convolution Neural Network Algorithm for MRI images of different patients.

Different types of image processing techniques like

segmentation, image enhancement and feature extraction are used for the brain tumor detection in the MRI images of the cancer-affected patients. Detecting Brain tumor using Image Processing techniques it involves the four stages is image preprocessing, image segmentation, feature extraction, and Classification. Image processing and neural network techniques are used for improve the performance of detecting and classifying brain tumor in MRI images.

2. Background Motivation

The detection and segmentation of brain tumors in medical images is a challenging task, and it plays a critical role in early diagnosis, treatment planning, and monitoring of tumor progression. Accurate detection and segmentation of brain tumors can assist radiologists and clinicians in making accurate diagnoses, planning surgeries, and predicting patient outcomes. However, manual detection and segmentation of brain tumors in medical images can be time-consuming, subjective, and prone to human error.

In recent years, there has been a growing interest in using machine learning algorithms, specifically deep learning and convolutional neural network (CNN) algorithms, for the automatic detection and segmentation of brain tumors in medical images. Deep learning algorithms can learn complex representations of medical images and extract relevant features for accurate tumor detection and segmentation. CNNs, in particular, have shown promise in various image processing tasks, including image classification, segmentation, and object detection.

The motivation behind using deep learning and CNN algorithms for brain tumor detection is to improve the accuracy, efficiency, and reproducibility of tumor detection and segmentation in medical images. This can help radiologists and clinicians make more accurate diagnoses, plan more effective treatments, and improve patient outcomes. Moreover, deep learning algorithms can be trained using large datasets, and they can learn to identify patterns and features that are difficult for human experts to discern, which can help to identify tumors that may be missed by human observers.

Overall, the motivation behind brain tumor detection using deep learning and CNN algorithms is to provide an automated

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and objective approach for accurate tumor detection and segmentation in medical images, which can improve the efficiency and accuracy of diagnosis, treatment planning, and monitoring of brain tumor.

3. Data Preprocessing

A. Resizing

Resizing the data in brain tumor detection using deep learning and CNN algorithms refers to the process of changing the size of the input images used for training and testing the deep learning model. Resizing is an important step in preprocessing the medical images before feeding them into the deep learning model. The size of the medical images can vary, and deep learning models typically require input images of a fixed size. Therefore, resizing is necessary to ensure that all images are of the same size before they are fed into the model. Resizing can also have an impact on the performance of the deep learning model. Resizing images to a smaller size can reduce the computational requirements of the model, allowing it to process more images in less time. However, resizing can also result in a loss of detail and information in the image, which can impact the accuracy of the model. It is important to balance the size of the input images with the performance of the model. Typically, the input images are resized to a fixed size that is large enough to retain important details while also being computationally efficient for the deep learning model. The optimal size for resizing the input images can depend on the specific deep learning architecture used and the characteristics of the medical images being analyzed.

B. Separate Data

The separation of data typically refers to dividing a dataset into two or more subsets for training, validation, and testing purposes. This is a common practice in machine learning to avoid overfitting and ensure the generalization of the model.

The most common way to separate the data is to split the dataset into three subsets: training set, validation set, and test set. The training set is used to train the model, the validation set is used to tune the hyperparameters and evaluate the performance during the training process, and the test set is used to evaluate the final performance of the model after the training is completed.

The splitting of the data can be done randomly or in a predefined manner. A common approach is to use a random seed to ensure that the same split is obtained each time the data is separated.

C. Re-Shape Data

Reshaping the data is an important step in preparing the input data for brain tumor detection using deep learning and CNN algorithms. This step involves changing the shape of the input data to a format that can be processed by the deep learning model. The input data for a deep learning model typically consists of images or other forms of data that are represented as multi-dimensional arrays or tensors. The shape of these arrays depends on the size and dimensions of the input data. In the case of medical images used in brain tumor detection, the input data is usually represented as a three- dimensional array, with dimensions representing the width, height, and depth of the image. Reshaping the data involves modifying the shape of the input array to match the requirements of the deep learning model. This may involve flattening the input data into a onedimensional array or reshaping it into a different shape that can be processed by the model. And there are some reasons for the re-shaping the data i.e., Matching the input shape of model, reducing the computational requirements, and normalizing the data.

D. Flattening

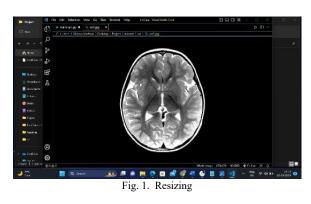
Flattening the data is an important step in preparing the input data for brain tumor detection using deep learning and CNN algorithms. This step involves converting the input data, which is typically represented as a multi-dimensional array, into a onedimensional array or vector. The reason for flattening the data is to reduce the complexity of the input data and make it easier for the deep learning model to process. Deep learning models typically operate on one-dimensional input data, such as a vector of input values. Flattening the input data into a vector helps to ensure that the model can process the data efficiently and effectively.

E. Convolution Neural Network

CNN (Convolutional Neural Network) is a deep learning algorithm that has been widely used in image processing and computer vision tasks, including brain tumor detection. The CNN algorithm is designed to automatically learn features and patterns from images by using multiple layers of convolutional filters and pooling operations. In the context of brain tumor detection using CNN algorithms, the input data typically consists of medical images such as MRI scans. The CNN algorithm takes the input images and passes them through a series of convolutional layers, which are designed to extract features and patterns from the input data. Each convolutional layer consists of a set of filters that are applied to the input data. These filters are designed to detect specific features or patterns in the input data, such as edges, shapes, or textures. The output of each convolutional layer is passed through a non-linear activation function, such as ReLU (Rectified Linear Unit), which helps to introduce non-linearity into the model and improve its ability to learn complex features. After passing through the convolutional layers, the output is passed through one or more pooling layers. Pooling layers help to reduce the dimensionality of the output data by down sampling the data, which can help to reduce the computational requirements of the model and prevent overfitting. The output of the pooling layers is then flattened into a one-dimensional vector and passed through one or more fully connected layers. Fully connected layers are used to classify the input data and make predictions about the presence or absence of a brain tumor. During training, the CNN algorithm uses backpropagation and gradient descent to update the weights and biases of the model, in order to minimize the difference between the predicted output and the true output.

F. Preprocessing Results

These are the preprocessing results.



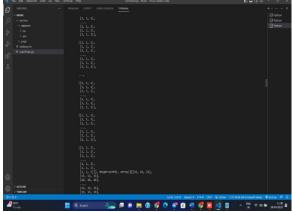


Fig. 2. Separate data

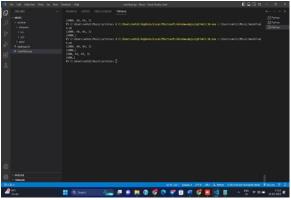


Fig. 3. Re-Shape data



Fig. 4. Flatten

G. Testing Result

If the person is affected with Brain Tumor, then the result will be declared in probability form i.e., either '0' or '1'.

4. Result

Based on the web development, when we declare an image, it compares the testing result. Based on the testing result it declares whether the person is affected with brain tumor or not.

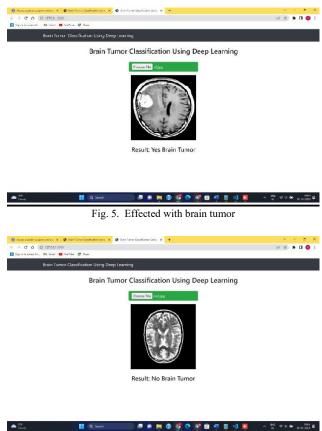


Fig. 6. Not effected with brain tumor

5. Conclusion

CNN algorithms are particularly effective in detecting brain tumors from magnetic resonance imaging (MRI) scans. They can automatically learn features from the image data and use this information to classify the images as either tumor or nontumor. This can greatly reduce the time and effort required for manual analysis of the MRI scans. Studies have shown that CNN algorithms have achieved high accuracy rates in detecting brain tumors, with some achieving accuracies of over 95%. These results suggest that CNN algorithms can be a valuable tool for radiologists and physicians in the early detection of brain tumors. In conclusion, the use of deep learning and CNN algorithms for brain tumor detection has shown great promise and has the potential to revolutionize the field of radiology. With further development and optimization, these techniques could greatly improve patient outcomes by enabling earlier detection and treatment of brain tumors.

References

- Wang, G., Li, W., Ourselin, S., Vercauteren, T., & Lian, J. (2019). Automatic brain tumor detection and segmentation using U-Net based fully convolutional networks. In Annual Conference on Medical Image Understanding and Analysis (pp. 745-755). Springer.
- [2] Kamble, A., & Mahajan, S. (2020). Brain tumor detection using convolutional neural network. In Proceedings of the 2020 International Conference on Computer Science, Engineering and Applications (pp. 373-380). Springer.
- [3] Guo, Y., Liu, Y., Oerlemans, A., Lao, S., Wu, S., & Lew, M. S. (2016). Deep learning for visual understanding: A review. Neurocomputing, 187, 27-48.
- [4] Chang, K., Balachandar, N., Lam, C., Yi, D., Brown, J., Beers, A., & Rubin, D. (2018). Distributed deep learning networks among institutions for medical imaging. Journal of the American Medical Informatics Association, 25(8), 945-954.
- [5] Havaei, M., Davy, A., Warde-Farley, D., Biard, A., Courville, A., Bengio, Y., & Pal, C. (2017). Brain tumor segmentation with deep neural networks. Medical image analysis, 35, 18-31.
- [6] N. Gordillo, E. Montseny, and P. Sobrevilla, "State of the art survey on MRI brain tumor segmentation," Magnetic Resonance Imaging, vol. 31, no. 8, pp. 1426–1438, 2013.
- [7] A. Demirhan, M. Toru, and I. Guler, "Segmentation of tumor and edema along with healthy tissues of brain using wavelets and neural networks," IEEE Journal of Biomedical and Health Informatics, vol. 19, no. 4, pp. 1451–1458, 2015.