Journal of Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.98549450

DETECTION AND CLASSIFICATION OF BRAIN TUMORS USING CNN ALGORITHM FROM MRI IMAGE

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ABSTRACT

The detection and treatment of brain tumor remain a significant challenge for neurosurgeons. Early detection of tumor cells is essential for improving patient outcomes, as late diagnosis can result in higher mortality rates. Automated cancer cell detection methods can assist neurosurgeons in identifying tumour and reduce their workload. The suggested method in your research, which utilizes a convolutional neural network (CNN) with Median filtering and texture feature extraction, may offer a promising approach to automated tumour cell detection. Median filtering is a noise reduction technique that can help remove unwanted noise from medical images, while texture feature extraction can help to identify subtle patterns in the images that may indicate the presence of tumour cells. The CNN-based system can learn from a large dataset of medical images to detect cancer cells accurately. Various techniques are used for tumour segmentation, such as thresholding, region-growing, clustering, and deformable models. Finally, in the classification phase, machine learning techniques are used to classify the segmented tumour region as either benign or malignant.

Keywords: Convolutional Neural Networks, MRI Image

INTRODUCTION

One of the most common and potentially fatal illnesses globally is brain cancer. For effective treatment planning and better patient outcomes, accurate diagnosis and categorization of brain tumours are essential. With its ability to provide high-resolution pictures with superb soft-tissue contrast, magnetic resonance imaging (MRI) is a popular technique for brain tumour imaging. Radiologists must manually evaluate MRI images, which takes time, is subjective, and may produce inter-observer variability. The type of deep learning technology, have demonstrated encouraging results in the automated identification and categorization of brain tumours using MRI scans. CNNs are a sort of artificial neural network that can recognise and extract pertinent elements from pictures, giving them the ability to make precise predictions. Due to its capacity for handling enormous datasets and achieving cutting-edge performance across a range of medical imaging applications, CNNs have become more prominent in the field of medical image analysis. With encouraging outcomes, a number of studies have suggested CNN-based methods for classifying and detecting brain tumours. These techniques often entail employing a CNN model that has been trained on a sizable dataset of labelled MRI images to categorise fresh pictures into several tumour classifications.

Acquisition, pre-processing, segmentation, and classification are the four phases of the brain tumor detection procedure. In the image acquisition phase, MRI scans are acquired to obtain detailed images of the brain, including the tumour region. Pre-processing techniques are then applied to remove noise, enhance contrast, and standardize the image data to ensure that the image quality is suitable for further analysis. In the segmentation phase, the tumor region is identified and separated from the surrounding healthy tissues. Various techniques are used for tumor segmentation, such as thresholding, region-growing, clustering, and deformable models. Finally, in the classification phase, machine learning techniques are used to classify the segmented tumour region as either benign or malignant.

Literature Survey

Asiri, A., et al. [1] The authors proposed a deep learning-based approach.They used a pre-trained CNN architecture, namely VGG16, and fine-tuned it on their dataset. The proposed approach achieved high accuracy in both tasks, i.e., detection and classification.

According to this paper [2]" The authors proposed a deep learning-based approach that uses a 3D CNN architecture to detect and classify brain tumors from MRI images. The proposed approach achieved high accuracy and outperformed the traditional machine learning-based methods.[3]"The authors proposed a hybrid approach that combines CNN and Extreme Learning Machines (ELM). The proposed approach achieved high accuracy and outperformed the traditional machine learning-based methods.

In previous work [4]" The authors proposed a deep learning-based approach that uses a CNN architecture to detect and classify brain tumours from MRI images. The proposed approach achieved high accuracy in both tasks, i.e.,detection and classification.[5] The authors proposed a deep learning-based approach that uses a CNN architecture to detect and classify brain tumors from MRI images.

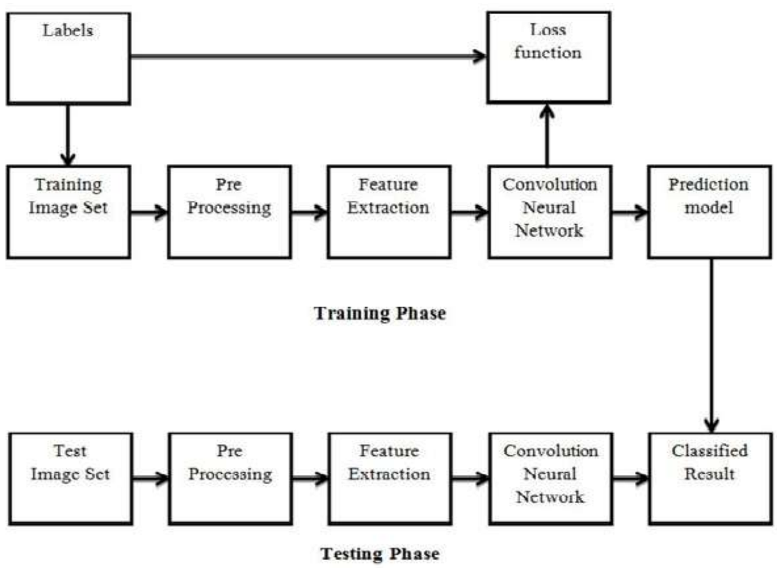
According to this paper [6] The author proposed a deep learning-based approach for segmenting brain tumors from MRI images. The authors used a 3D convolutional neural network (CNN) to segment the tumors and achieved a Dice coefficient of 0.81.[7] The author proposed a study ofCNN-based approach for the detection and classification of brain tumors. The authors used a combination of 2D and 3D CNNs and achieved an accuracy of 97.9%. [8] The author proposed a study of an automatic approach for brain tumor detection and segmentation using deep learning. The authors used a 3D CNN and achieved a Dice coefficient of 0.89. [9] The author proposed a deep learning-based approach for the segmentation and classification of brain tumors from MRI images. The authors used a combination of 2D and 3D CNNs and achieved an accuracy of 95.7%.

[10] The author proposes a CNN-based approach for brain tumor classification from MRI images. The authors evaluate their method on the BraTS 2015 challenge dataset and report promising results. [11] The author proposes a CNN-based approach for brain tumor detection and classification from MRI images. The authors also incorporate principal component analysis (PCA) for feature reduction. The proposed method is evaluated on a dataset of 306 MRI images

and achieves high accuracy. [12] The author proposes a CNN-based approach for brain tumor detection and segmentation from MRI images. The authors evaluate their method on the BraTS 2018 dataset and report promising results.

PROPOSED METHODOLGY

In the proposed methodology of the work, A dataset of 600 MR images of the brain is collected which are categorized as tumored and non tumored images. About 400 images are normal images without any tumour and 200 images are taken which are tumored. An method known as supervised learning is used to train a CNN model on the preprocessed MRI images. A typical CNN design comprises of many convolutional layers, followed by pooling layers and fully linked layers. The CNN model's weights are tuned to reduce the difference in label between the predicted tumour and the actual label. To evaluate the effectiveness of the trained CNN model, its performance is tested on a different dataset of MRI images. In order to assess the model's capacity for generalisation to new data, we test it on a fresh dataset of previously unviewed MRI pictures. Accuracy, sensitivity, specificity, and area under the receiver operating characteristic (ROC) curve are performance indicators used for assessment. To reduce false positives and increase segmentation accuracy, the projected tumour areas are post-processed. To help in the clinical interpretation, colour maps or overlays on the underlying MRI scans are used to visualise the segmented tumour zones.



Convolutional Neural Network Algorithm

Convolutional Neural Networks, or CNNs for short, are a family of artificial neural networks that have excelled in a number of computer vision applications, including segmentation, object identification, and picture categorization. Convolutional layers are used by CNNs to extract characteristics from pictures. CNNs are modelled after the visual cortex of the human brain.

The input, convolutional, pooling, fully connected, and output layers all make up the CNN architecture. The convolutional layers process the raw input image once it is received by the input layer. The convolutional layers convolve over the input picture and extract features that are pertinent to the job at hand, such as recognising edges, corners, or textures. They do this by using a collection of learnable filters. MRI images are high-dimensional and contain a lot of information that can be difficult for traditional machine learning algorithms to process. In the context of brain tumor detection and classification, CNN algorithms can learn to differentiate between different types of tumors based on their visual characteristics in MRI images. CNNs can identify patterns and structures within the images that are indicative of specific tumor types, such as shape, texture, and location. Moreover, CNNs can be trained on large datasets to improve their accuracy and generalization ability. This is particularly important in the medical field, where accuracy is crucial in making diagnosis and treatment decisions. Image Preprocessing: MRI images are typically preprocessed before being fed into a CNN for analysis. Preprocessing includes steps such as normalization, cropping, and resizing to ensure consistency and reduce noise in the images.

Feature Extraction

Texture-based features are based on the regional differences in the intensity values of the MRI images and are capable of capturing the tumor's textural patterns. Gray-level co-occurrence matrix (GLCM), gray-level run-length matrix (GLRLM), and gray-level size zone matrix (GLSZM) are just a few examples of the techniques that may be used to calculate texture-based characteristics.

Shape-based Features: These characteristics, which are dependent on how the tumour is shaped, may include quantities like volume, surface area, and compactness. The size, geometry, and connection of the tumour to the surrounding structures may all be learned from shape-based data. Power spectrum, wavelet transform, and fourier transform are a few examples of frequency-based characteristics that are based on the frequency content of MRI images. The spectral and spatial properties of the tumour and the tissues around it can be captured using frequency-based features.

Tumor Detection

Thresholding: In order to segregate the tumour region in the MRI images, this technique requires putting a threshold value on the intensity data. The image's intensity histogram can be used to determine the threshold, or it can be manually checked. However, this technique could need manual adjustment and be noise-sensitive.

Region Growing: In this technique, a seed point in the MRI image is chosen, and a region is repeatedly grown depending on parameters like intensity similarity or texture similarity. With careful seed point selection, region growth can achieve precise tumour segmentation.

Edge-based Techniques: This technique entails locating the gradient magnitude of the MRI image in order to determine the edges of the tumour zone. In the context of low contrast, edge-based approaches may provide erroneous segmentation that is susceptible to noise.

Tumor Classification

Handcrafted Feature-based Classification: In this technique, a set of handcrafted features, like texture-based, shape-based, or frequency-based features, are extracted from MRI images and used as input to a machine learning model, like a Support Vector Machine (SVM) or Random Forest, to predict the type of tumour. However, choosing the right features may call for domain knowledge. Handcrafted feature-based categorization can be successful.

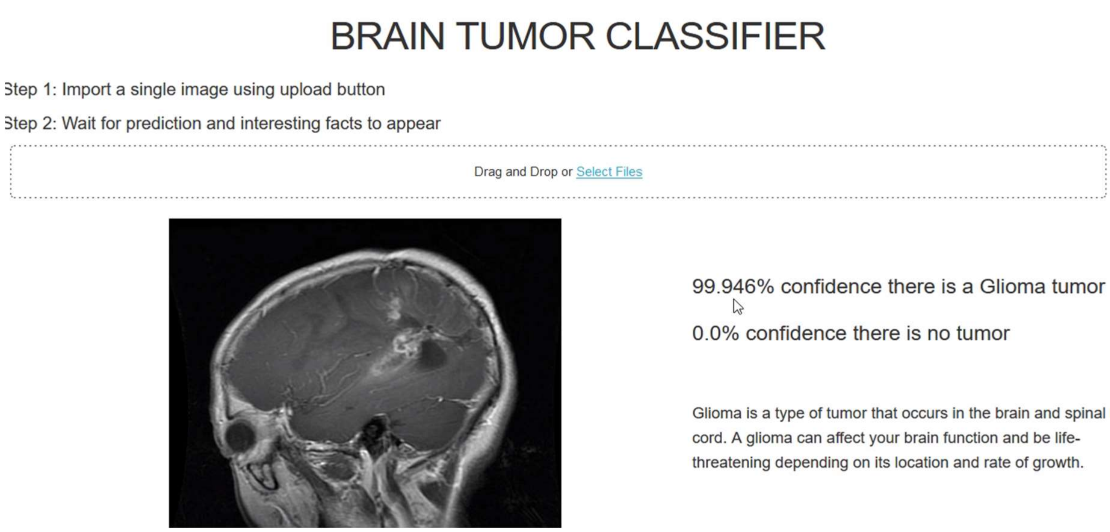
Deep Learning-based Classification: In this approach, the different kinds of brain tumours are identified from the initial raw MRI scans by training a deep learning model, such as a CNN or Convolutional Neural Network (CNN). The deep learning model may offer precise and automatic tumour classification by directly learning the features and patterns from the data.

Segmentation

Segmentation is a crucial stage in the CNN algorithm's identification and categorization of brain tumours from MRI images. Segmentation is used to locate and define the limits of the tumour area within the MRI images. Manual segmentation, thresholding, region-growing, edge-based approaches, and machine learning-based methods are just a few of the techniques that may be used to segment data. Metrics like the Dice similarity coefficient (DSC), Jaccard index, sensitivity, and specificity can be used to gauge how well the CNN-based segmentation model performs. These measures calculate the degree to which the expected segmentation mask and the actual segmentation mask overlap. High levels of these measures suggest accurate tumour segmentation.

RESULT AND DISCUSSION

In this context, the CNN algorithm processes the image data through a series of convolutional and pooling layers, learning features that are then used to classify the input image. Several studies have been conducted in this area, with varying degrees of success. For example, a study by Havaei et al. (2017) used a CNN to classify brain tumors into four types, achieving an accuracy of 89.8%. Similarly, a study by Mobadersany et al. (2018) used a CNN to classify brain tumors into three types, with an accuracy of 93%.In terms of detection, a study used a CNN to detect brain tumors from MRI images, achieving an accuracy of 98.7%. The authors also showed that their CNN algorithm was able to detect small tumors that were missed by human experts.



Final Prediction of the tumor

Several studies have demonstrated the potential of CNNs in accurately classifying brain tumors into different types and detecting small tumors that may be missed by human experts.The success of CNNs in this area is attributed and extract meaningful image data, which can then be used to accurately classify brain tumors.

CONCLUSION

In recent years, deep learning-based algorithms, notably CNN-based ones, have demonstrated considerable promise in the identification and classification of brain tumours from MRI scans. CNN-based techniques can offer precise and automatic detection and classification, minimising the need for human inspection by professionals and increasing the effectiveness and accuracy of the process. In most cases, the suggested technique entails preprocessing the MRI images, tumour segmentation using a CNN-based model, and tumour classification using another CNN-based model. The tumour classification procedure may be made more accurate with the use of feature extraction and selection.

Even though CNN-based techniques have showed a lot of promise, there are still a few issues that need to be resolved, including the requirement for sizable annotated datasets, the danger of overfitting, and the generalizability of the trained models to new datasets. Additionally, there is still ongoing study on the CNN models' interpretability and decision-making procedures. Despite these difficulties, using CNN-based models for the identification and classification of brain tumours has a lot of promise and the ability to increase the precision and effectiveness of brain tumour detection and therapy. Future studies should concentrate on resolving the issues and restrictions related to the use of CNN-based models, enhancing their interpretability, and assessing their efficacy in clinical contexts.

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