Brain Tumor Detection Using Convolutional Neural Networks in MRI Images

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ABSTRACT: Brain tumors are the most common and aggressive disease, leading to a very short life expectancy at its highest degree. Therefore, treatment planning is a critical step in improving the quality of life of patients. Generally, various imaging techniques such as computed tomography (CT), magnetic resonance imaging (MRI) and ultrasound are used to evaluate the tumor in a brain, lung, liver, breast, prostate, etc. Especially in this work, MRI scans are used to diagnose tumors in the brain. However, the sheer amount of data generated by MRI images frustrates the manual classification of tumors versus non-tumors at any given time. But it has some limitations (that is, precise quantitative measurements are provided for a limited number of images). Therefore, automatic and reliable classification schemes are essential to prevent the mortality rate of humans. The automatic classification of brain tumors is a very challenging task in the great spatial and structural variability of the surrounding region of the brain tumor. In this work, we propose the automatic detection of brain tumors using the classification of tumor, Che convolutional neural network (CNN). If a tumor is detected, the system classifies the tumor and tells the patient what stage of the cancer they are likely to have.

Keywords: MRI, brain NN, feature extraction, classification

I. INTRODUCTION

Brain tumour is one of the vital organs of the human body, made up of billions of cells. The abnormal group of cells is formed from the uncontrolled division of cells, which is also called a brain tumor. Brain tumor are divided into two types, as low-grade (grade 1 and grade 2) and high-grade (grade 3 and grade 4) tumor. Low-grade brain tumor are called benign. Similarly, a high-grade tumor is also called malignant. The benign tumor is not a cancerous tumor. Therefore, it does not spread to other parts of the brain. However, the malignant tumor is cancerous. Hence it spreads rapidly with indefinite limits to other body regions with ease. Leads to immediate death 12

Brain MRI is primarily used for tumor detection and the process of tumor progress. This information is mainly used for tumor detection and treatment processes. MRI provides more information about a given medical image than CT or ultrasound. MRI provides detailed information on the structure of the brain and the detection of abnormalities in the brain tissue. In contrast, neural networks (NN) and the support vector machine (SVM)

are the methods commonly used for its good implementation in recent years.11 However, recently, Deep Learning (DL)

Models set a trend in machine learning, as underground architecture can efficiently represent complex relationships without the need for a large number of nodes as in surface architectures, e.g. Nearest Neighbor K (KNN) and Support Vector Machine (SVM). As a result, they have rapidly grown to become state of the art in several areas of health informatics, such as medical image analysis, medical informatics, and bioinformatics.

A brain tumor can be primary or secondary. A primary brain tumor originates in the brain itself or in tissues adjacent to it, i.e. the membranes that cover the brain (meninges), cranial nerves, pituitary gland, or pineal gland, while a secondary brain tumor develops when cells cancers of other organs such as lung, kidney, breast, etc. spread to the brain [3]. Primary brain tumors initially arise due to mutations in their DNA. These mutations allow the abnormal cell to grow and the normal cell to die. It can cause brain damage and can sometimes be life-threatening. In this work, we proposed a CNN model capable of accurately classifying the brain tumor. Therefore, cancer treatment can be started at an early stage. A reliable method of segmenting the tumor would clearly be a useful tool. Currently, however, there is no widely accepted method in clinical practice for quantifying tumor volumes

from MRI. The main goal of this work is to detect the brain tumor from the magnetic resonance image and calculate its area and identify the stage of the tumor which is easier. reducible costs and save time.
brain tumor is uncontrolled growth of cells. Furthermore, the localization of the tumor within the brain has a profound effect on the patient's symptoms, surgical treatment options and the likelihood of obtaining a definitive diagnosis.There are some algorithms such as the threshold method, the growth of the region, which it uses only the k-means algorithm, but all these algorithms cannot extract all the fine spatial features

from the MRI image.therefore, there is a problem
with these algorithms,as they do not properly detect the brain tumor image.

II. LITERATURE SURVEY

The main motivation for article [1] is to introduce a class of robust non-Euclidean distance measures for the original data space to derive a new objective function and then group the non-Euclidean structures in the data to improve the robustness of the original grouping algorithms to reduce noise and outliers.

The article [2] presents a validation study on statistical techniques for the classification of unsupervised brain tissue in magnetic resonance imaging (MRI). Various image models are evaluated by assuming different assumptions about the intensity distribution model, the spatial model and the number of classes. The methods are tested on simulated data for which the truth of the classification medium is known. Different intensities and non-uniformities of noise are added to simulate real image conditions. No image quality improvement is considered before or during the sorting process.

In [3] a variation of the fuzzy c-means (FCM) algorithm that provides image clustering is proposed. The proposed algorithm incorporates local spatial information and grayscale information in a new and fuzzy way. Experiments with real and synthetic images show that the FLICM algorithm is effective and efficient, providing robustness to noisy images.

The article [4] presents an unsupervised and distribution-free change detection approach for synthetic aperture radar (SAR) imaging based on an image fusion strategy and a novel fuzzy clustering algorithm. The image blending technique is introduced to generate a different image using complementary information from a medium aspect ratio image and a log ratio image. Experiments with real SAR images show that the image fusion strategy integrates the advantages of the log ratio operator and the average ratio operator and achieves better performance.

In [5], an improved FCM method based on spatial information for target segmentation of infrared vessels is proposed. The enhancements include two parts: 1) adding the non-local spatial information based on the ship's target and 2) using the spatial shape information from the ship's target outline to refine the local spatial constraint using the random Markov field. In addition, the results of the K averages are used to initialize the advanced FCM method. Experimental results show that the improved method is efficient and works better than existing methods, including existing FCM methods, for segmenting IR vessel images.

Medical image classification has gained a lot of attention in recent years, and the convolutional neural network (CNN) is the most popular neural network model for image classification problems. CNN is designed to adaptively determine features through back-propagation by applying numerous building blocks, such as convolution levels, grouping levels, and fully connected levels. In [6], the author focused primarily on developing a CNN model for classifying brain tumors on T1-weighted contrast-weighted MRI. The proposed system consists of two important steps. First, pre-process the images using different image processing techniques, then classify the pre-processed image using CNN. The experiment is performed on a dataset of 3064 images containing three types of brain tumors (glioma, meningioma, pituitary). We achieved high test accuracy of 94.39%, average accuracy of 93.33%, and average recovery of 93% using our CNN model. The proposed system showed satisfactory accuracy in the dataset and outperformed many of the main existing methods.

Brain tumors are the most common and aggressive disease, leading to a very short life expectancy at its highest degree. Therefore, treatment planning is a critical step in improving the quality of life of patients. In general, various imaging techniques such as computed tomography (CT), magnetic resonance

Imaging (MRI) and ultrasound images are used to evaluate the tumor in the brain, lung, liver, breast, prostate, etc. Especially in this work, MRI scans are used to diagnose tumors in the brain. However, the sheer amount of data generated by MRI images frustrates the manual classification of tumors versus non-tumors at any given time. But it has some limitations (that is, precise quantitative measurements are provided for a limited number of images). Therefore, automatic and reliable classification schemes are essential to prevent the mortality rate of humans. The automatic classification of brain tumors is a very challenging task in the great spatial and structural variability of the surrounding region of the brain tumor. In [7], automatic detection of brain tumors using the classification of the convolutional neural network (CNN) is proposed. The deeper architectural design is done through the use of small cores. The weight of the neuron is given as small. Experimental results show that CNN files are 97.5% accurate with low complexity and compared to all other state-of-the-art methods.

III. PROPOSED SYSTEM

The main objective of this research work is to design an efficient automatic classification of brain tumors with high accuracy, performance and low complexity. In conventional brain tumor, classification is performed using Fuzzy C Means (FCM) based segmentation, structure and shape feature extraction, and SVM and DNN based classification. The complexity is low. But the computation time is high while the accuracy is low. Furthermore, to improve accuracy and reduce computation times, a classification based on convolutional neural networks is introduced in the proposed scheme.

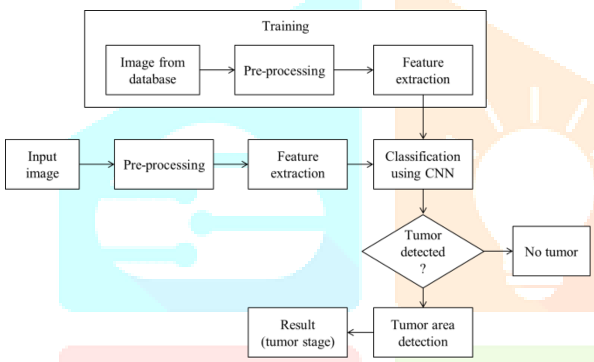

Fig proposed system

The input image could be a information image (for training) and a period of time image (brain neoplasm detection). Preprocessing could be a common name for operations on pictures at all-time low level of abstraction, each input and output ar intensity pictures. The goal of preprocessing is a picture information improvement that removes unwanted distortions or improves some image characteristics necessary for post-processing. Before discussing feature purpose extraction, you would like to own a live to check components of pictures. The extraction and matching of characteristics relies on these measures. additionally to the one purpose feature, a additional advanced feature kind is additionally introduced. The feature extraction technique is employed to extract options whereas retentive the maximum amount data as potential from an oversized set of image information. A dataset is provided to coach CNN. The assessment is completed via CNN.

IV. CONCLUSION

The classification of brain tumors is very important in the field of medical science. In this article, we focus on developing a CNN classifier that classifies tumors. Initially, the proposed system pre-processes the image data. Pre-processing includes image filtering. The system then classifies the images using the CNN model. In addition, the classification results are provided as normal images of the brain or tumor. CNN is one of the deep learning methods, containing layered feedback sequences. The Python language is also used for the implementation.

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