



Brain Tumor Detection

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Abstract:

Brain tumors, also known as neoplasms, are abnormal cells that grow within the brain. One of the most common and effective ways to detect these tumors is through Magnetic Resonance Imaging (MRI) scans. These scans allow doctors to identify any abnormal tissue growth within the brain. Advances in technology have led to the use of Machine Learning and Deep Learning algorithms to analyze MRI images for more efficient and accurate detection of brain tumors. This can greatly aid in the treatment of patients and help radiologists make quick decisions. In this proposed research, we will examine the use of a self-designed Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) to detect the presence of brain tumors, and assess their effectiveness.

INTRODUCTION

Detection and classification of brain tumor is a challenging task in the field of medical image processing. One of the most widely used method to detect brain tumors is through MRI scans. These scans provide detailed information about the soft tissues in the brain, which is crucial for diagnosis of tumors. Accurate segmentation of these images is essential in diagnosis of brain tumors using computerized -assisted tools. This research focuses on designing an efficient and accurate approach for detecting tumors in brain MRI scans, and if present, classifying them as benign or malignant. Experiments conducted show that the proposed method has a higher accuracy than existing methods for classifying tumor types. Two different methods are proposed in this project, segmentation of tumor and determination of its type: SOM Clustering and SVM Classification. Each MRI image is preprocessed to remove noise and enhance contrast before being passed through the proposed segmentation techniques. The `ginput()` command was used to retrieve the foreground points' pixel values from a texture image, and these values were used to

represent the tumor region. The `rangefilt()` method creates a texture image, which is then enhanced by the application of a smoothing filter to bring out more of the texture properties. A major challenge faced in this project is accurately locating and extracting the tumor region from the image. Unnecessary white portions of the image can be falsely segmented as a tumor due to lighting issues, while reduced contrast and noise can cause regions of the image to be falsely identified as a tumor. Additionally, the grade of the MRI image may be degraded due to complications that could occur during the scanning stage.

Problem Statement

Nowadays, tumors can be life-threatening, and brain tumors are among the most dangerous. These tumors can present in various shapes, sizes, locations, and intensities, making detection and diagnosis a complex task. Due to the lack of precise quantitative criteria to categorise the images as brain tumours or not, the manual classification of tumours from Magnetic Resonance Imaging scans is subjective, and the results can differ amongst experts. These problems can be resolved and more accurate findings can be obtained with automated brain tumour detection from MRI images. Medical professionals and pathologists have always found it extremely difficult to diagnose and plan for treatment for brain tumours based on the numerous symptoms of patients. Some tests can also be laborious, add to the workload for pathologists, and make it more challenging for them to provide correct results.

The current system has several limitations, including:

1. The need for a large amount of training data
2. The requirement of an appropriate model
3. The time-consuming nature of the process
4. The tedious and exhaustive nature of the procedure
5. The limitations of convolutional networks, which have been hindered by the size of the network considered.

Types of tumor we are detecting

Pituitary adenomas

Tumors that form in the pituitary gland, which is located at the base of the brain. These tumors are generally slow-growing and non-cancerous, and are classified based on their size or the type of cells from which they originate. Pituitary adenomas can be further categorized into three types: microadenomas (less than 10mm in size), macroadenomas (larger than 10mm), and giant tumors (larger than 40mm). They can either be functioning, which means the cells that make up the tumor lead to increased secretion of one or more hormones, or nonfunctioning, which means they do not secrete hormones but can compress surrounding areas of the pituitary gland, leading to hormonal deficiencies. The management of pituitary adenomas is done by a multidisciplinary team that includes specialists in endocrinology, ophthalmology, and neurosurgery.

Glioma

This is a type of brain or spinal cord tumor that originates from glial cells, which are cells that surround and assist nerve cells. As the tumor expands, it forms a mass that can press on brain or spinal cord tissue and cause symptoms, that varies depending on the location of the tumor. Gliomas can be classified into different types, some of which grow slowly and are considered not cancerous, while others are malignant and grow aggressively, invading healthy brain tissue. Some forms of glioma are more prevalent among adults, while others are more common among children. The exact type of glioma helps healthcare professionals determine the severity of the condition and the most appropriate treatment options, which may include surgery, radiation therapy, chemotherapy, and other therapies.

Meningioma

This is a type of tumor that originates from the meninges, the protective membranes that surround the brain and spinal cord. While not strictly a brain tumor, it can affect the brain and its surrounding structures by compressing or squeezing them. Meningiomas are the most common type of tumor that develops in the head. They tend to grow slowly and may not cause symptoms for many years. However, when symptoms do occur, they can be severe and include headaches, changes in vision, and seizures. Meningiomas are more common in women and are often found in older individuals, but can occur at any age. Due to their slow growth, meningiomas may not require immediate treatment and can be monitored over time. This project aims to detect the presence of brain tumors in MRI images and classify them as glioma, meningioma, no tumor, pituitary. The

process for achieving this goal can be broken down into several stages:

1. The first stage is obtaining MRI images of the brain.
2. Next, the images undergo pre-processing to prepare them for analysis.
3. Feature extraction is then performed to identify relevant characteristics of the images.
4. A segmentation technique is applied to isolate the tumor from the rest of the image.
5. Lastly, image analysis is conducted to classify the tumor as benign or malignant.

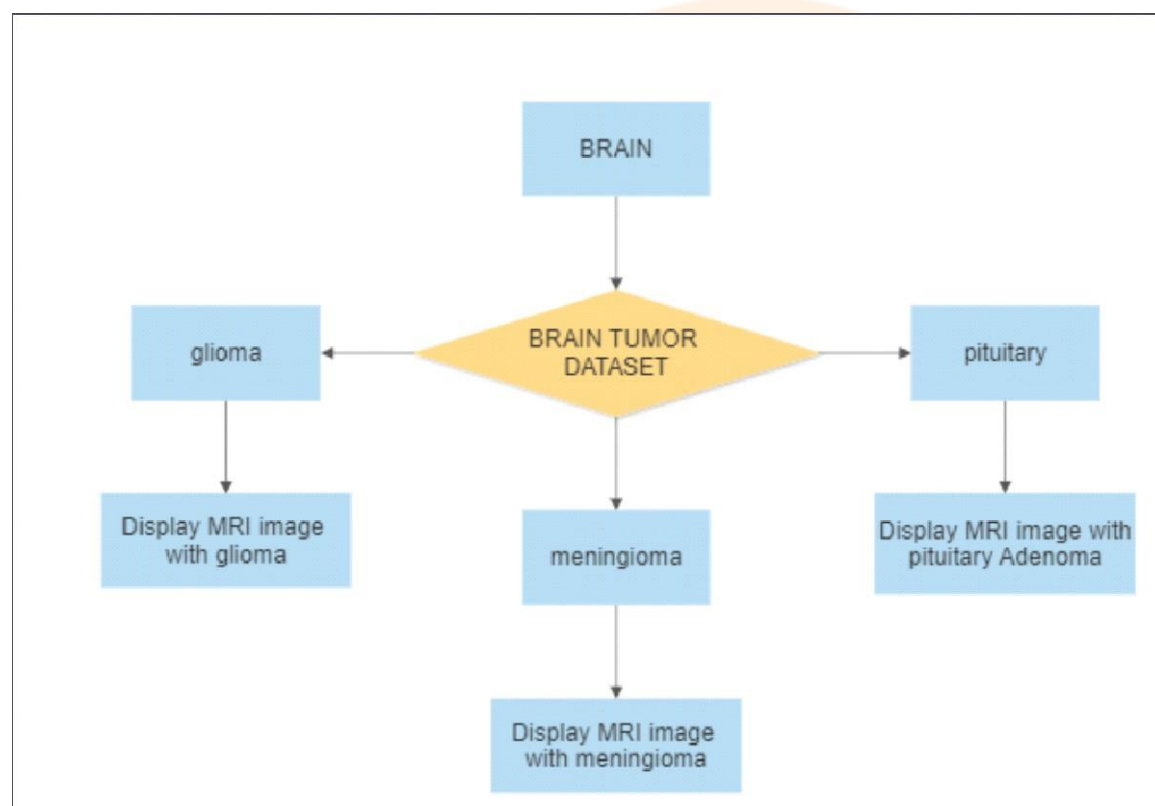
The input images will be processed through these stages and the final output will be the stage of the tumor.

LITERATURE REVIEW

A framework for tumor detection was proposed by Swapnil R. Telrandhe et al. [11] which uses image segmentation to separate the tumor from the background. Edge detection techniques were analyzed in the paper to determine their effectiveness for image segmentation. Another method for classifying brain tumors in MRI images was proposed by Malathi HongLong et al. [12], which utilizes wavelet entropy-based spider net plots and a probabilistic neural network for feature extraction and classification. Rajeshwari G. Tayade et al. [13] proposed a system that combines wavelet statistical features and co-occurrence wavelet texture features obtained from a two-level wavelet decomposition for classifying abnormal brain tissue as benign or malignant. Using a

combination of edge maps from morphological and wavelet methods, Lukas Let al. [14] proposed a method for primary brain tumour segmentation that identifies relevant feature points and uses a region-growing algorithm to separate the tumour region. The strategy works well and produces accurate segmentation results. Additional study can look into the methodology for automatically segmenting 3D tumours, segmenting ROIs in other medical images, and using the technology for retrieving medical images.

SYSTEM DESIGN AND FLOW



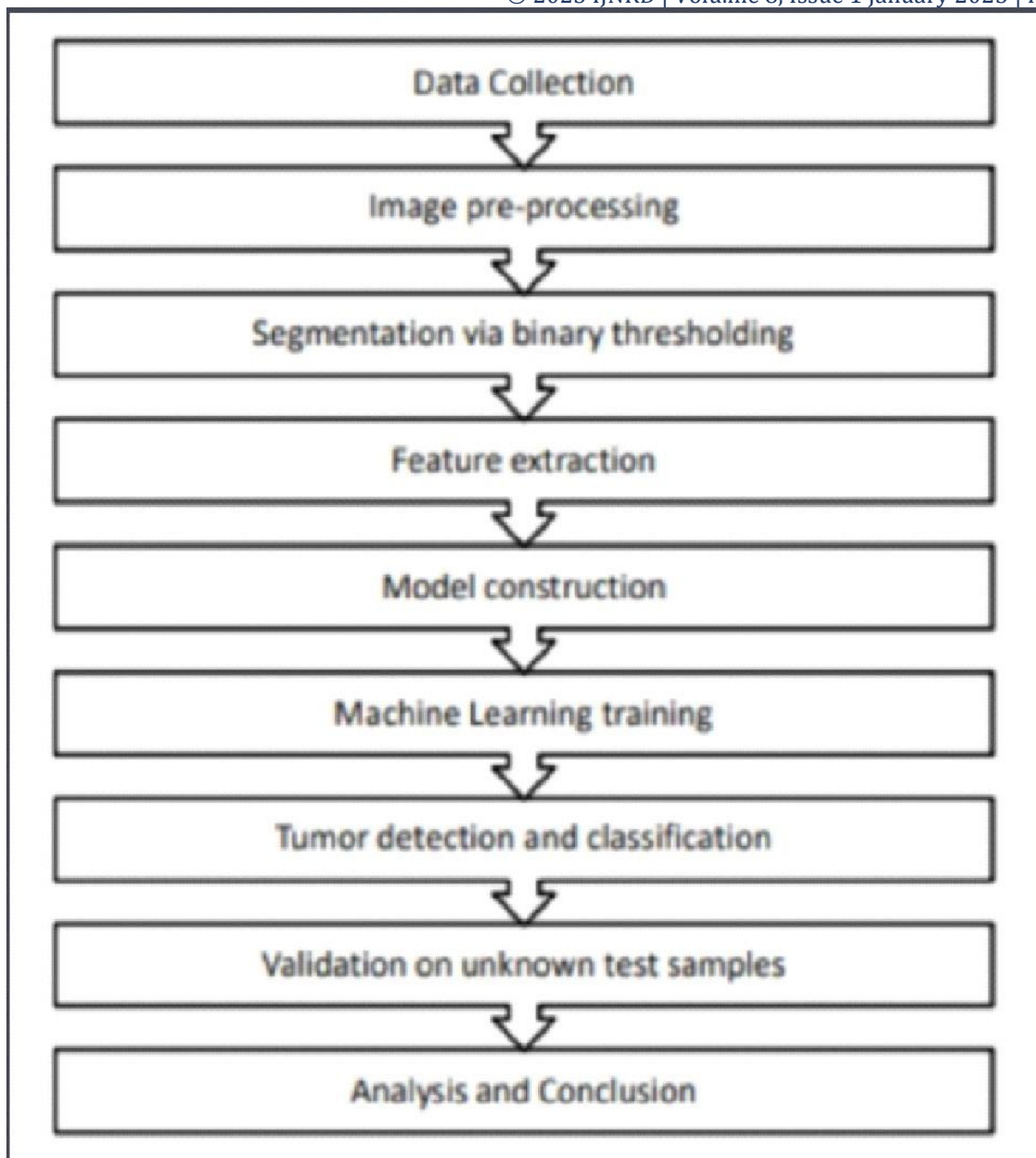


Fig Program Flowchart

In this paper, a technique called fuzzy C-means clustering is used to identify image areas that have the highest likelihood of containing a tumor. Additionally, a search heuristic called genetic algorithm (GA) is used to generate useful solutions to the problem of identifying brain tumors. Genetic algorithms belong to a broader category of evolutionary algorithms (EA) that use techniques inspired by natural evolution, such as inheritance, mutation, selection and crossover to find optimal solutions for optimization problems. According to the tumor's location, brain tumours may result from a breakdown in the regular rhythm of cell death and manifest a variety of symptoms. These tumours can disrupt normal brain function by putting pressure on the brain, moving or pressing the brain against the skull, and harming nerves and healthy brain tissue.

References

- [1]. L. Juo, L. zao, "Tumor detection in MR images using one-class immune feature weighted SVMs," IEEE Transactions on Magnetism, vol. 47, no. 10, pp. 3849–3852, 2011. View at: Publisher Site — Google Scholar.
- [2]. R.Kumari, "SVM classification an approach on detecting abnormality in brain MRI images," International Journal of Engineering Research and Applications, vol. 3, pp.1686–1690, 2013. View at: Google Scholar.
- [3]. 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. View at: Publisher Site — Google Scholar
- [4]. 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. View at: Publisher Site — Google Scholar

