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CEREBRAL INSIGHT: A CUTTING-EDGE APPROACH TO BRAIN TUMOUR SEGMENTATION USING UNIFIED NETWORKS AND EDGE DETECTION TECHNOLOGY

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ABSTRACT
Brain cancer segmentation is the technique of recognizing and distinguishing tumour tissue from healthy brain tissue in medical images such as magnetic resonance imaging (MRI). Accurate segmentation is crucial for diagnosing and treating brain tumours. Traditional brain tumour segmentation, which frequently requires an MRI scan conducted by a radiologist, is a manual procedure. While manual segmentation is not perfect, it is time-consuming and difficult, particularly for big or complicated tumours. Automated segmentation techniques based on deep learning algorithms have showed promise in recent years, offering a faster and more accurate alternative to manual segmentation. The study aims to create deep learning models for autonomous semantic image segmentation from brain MRI data. It utilizes CNNs, edge detection technology, and watershed techniques, evaluating on the BraTS dataset. Various regularization techniques and hyperparameters are being improved, with the goal of making the desktop applications easily accessible to medical practitioners.
Keywords: Brain Tumour, MRI images, Deep learning, CNN, Edge detection technology.

INTRODUCTION
A brain tumour is an abnormal cell growth in the brain, either benign or malignant, that impairs brain function and health. The World Health Organisation classifies gliomas, a frequent form, into four classes. High-grade gliomas are less likely to survive, whereas low-grade gliomas grow slowly and have a better prognosis. Early detection is critical. MRI is recommended because it is non-invasive and provides good soft tissue imaging. However, tumour variety complicates categorization. Accurate segmentation is essential for diagnosis and therapy planning. Methods include manual, semi-automatic, and completely automated techniques. Automation is necessary for efficiency but difficult owing to tumour unpredictability. The Brain Tumour Segmentation Challenge (BraTS) has made strides in addressing this issue. Convolutional neural networks have shown remarkable performance in image segmentation tasks, including brain tumour segmentation, surpassing human capabilities. The purpose of this project is to create an automated brain tumour segmentation application that generates segmentation masks from multimodal MRI scans of a patient's brain. The dataset used for segmentation is BRATS 20, which includes four different MRI modalities and one target mask file, resulting in an easy-to-use GUI for medical practitioners to execute automated glioma segmentation.

LITERATURE SURVEY
Swapnil R. Telrandhe et.al.[1], in their work titled as "Implementation of Brain Tumor Detection

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using Segmentation Algorithm & SVM", developed a system for detecting brain tumors in MRI images and distinguishing between malignant and benign regions. The system includes several stages MRI images undergo median filtering, morphological filtering for skull removal, and k- means segmentation. Object labeling and feature extraction utilize Histogram of Oriented Gradients (HOG), while data classification is performed by a linear Support Vector Machine (SVM). The project also employs a combination of median filter, morphological filter, and wavelet transform for preprocessing and skull masking, enhancing consistency compared to using these technologies separately. However, the project's main limitation is its lower accuracy, especially with large datasets.
Ali IúÕn et al. published a paper titled "Review of MRI-based brain tumour image segmentation using deep learning methods," highlighting the significance of brain tumour segmentation in medical image processing. Their research intends to explore MRI-based brain tumour segmentation approaches, emphasizing the rising popularity of deep learning for this purpose. Deep learning algorithms have outperformed conventional approaches, allowing for efficient processing and objective assessment of massive MRI datasets. Despite advances, automatic segmentation remains difficult, and future improvements in CNN architectures and the incorporation of complementary information from other imaging modalities such as PET, MRS, and DTI may improve current methods, leading to more clinically acceptable automatic glioma segmentation approaches for improved diagnosis.
Eman Abdel-Maksoud et.al.[3], in their work titled as "Brain tumor segmentation based on a hybrid clustering technique", The study presents an effective image segmentation strategy for identifying regions of interest in medical images, focusing on brain tumor detection. It combines the K-means clustering technique with the Fuzzy C-means algorithm, followed by thresholding and level set segmentation for accuracy. This approach minimizes computing time and calculates the initial cluster k value to enhance efficiency. The method has been validated through various trials, demonstrating its performance and time-saving capabilities. Future research will involve 3D assessment using 3D slicer. A limitation is the need to address challenges in intensity adjustment processes to further refine MRI brain tumor segmentation.
Xiaomei Zhao et.al.[4], in their work titled "A deep learning model integrating FCNNs and CRFs for brain tumor segmentation", they have proposed a unified framework to obtain segmentation results with appearance and spatial consistency. We train a deep learning-based segmentation model using 2D image patches and image slices in following steps: 1) training FCNNs using image patches; 2) training CRFs as Recurrent Neural Networks (CRF-RNN) using image slices with parameters of FCNNs fixed; and 3) fine-tuning the FCNNs and the CRF-RNN using image slices. Their experimental results have demonstrated adopting 3D CRF as a post-processing step could improve the tumor segmentation performance. Their ongoing study is to build a fully 3D network to further improve the tumor segmentation performance which is a limitation of this project.

EXISTING METHOD

Existing technology for detecting brain tumours using MRI scans. Let us break down the components: Preprocessing using Median. Filtering is a typical technique for removing noise from photographs while maintaining edges. This procedure helps to enhance the quality of MRI pictures, which can sometimes contain noise, before they are analysed further. Segmentation using the K-

Means Algorithm is the process of dividing a picture into several segments or areas. The K-Means method is a clustering approach commonly used in picture segmentation. It divides the picture into K clusters depending on pixel intensities, which can aid in separating various regions of interest, such as tumours, from the backdrop. Feature Extraction using Histogram of Oriented Gradients (HOG) is a feature descriptor used in computer vision and image processing to identify objects. It estimates the distribution of gradient orientations in certain areas of a picture. In the context of brain tumour identification, HOG can extract useful texture and shape information from segmented areas. Classification using Linear Support Vector Machine (SVM) is a supervised learning approach for classification tasks. In this system, SVM is likely to use HOG's extracted characteristics as input and

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learn to categorize them as tumour or non-tumor. The linear SVM variation is effective for this task, particularly when dealing with high-dimensional feature spaces such as those created by HOG. Overall, this system appears to follow a standard pipeline for medical image analysis, beginning with preprocessing to improve image quality, followed by segmentation to isolate relevant regions, feature extraction to capture important characteristics, and classification to make predictions based on the extracted feature.

PROPOSED METHOD

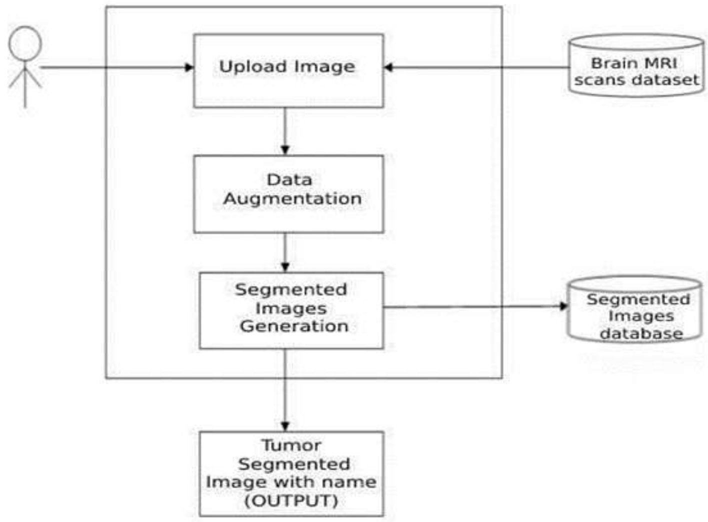
The architecture and methodology for developing an automated brain tumor segmentation application using CNNs (Convolutional Neural Networks) and marker-based watershed algorithm. Let's break down the components:

CNNs are a type of deep learning algorithm commonly used for image classification, detection, and segmentation tasks. They consist of multiple layers, including convolutional layers, rectified linear unit (ReLU) layers, and pooling layers. Convolutional layers apply convolution operations to the input image, extracting features such as edges, textures, and shapes. ReLU layers introduce non- linearity by applying the rectified linear unit activation function. Pooling layers down sample the feature maps, reducing spatial dimensions while retaining important features. After passing through several convolutional and pooling layers, the output is flattened and fed into a fully connected layer. This layer assigns class scores or probabilities to the input, enabling the network to classify the image into different classes. In the context of brain tumor segmentation, the classes typically represent tumor and non-tumor regions.

Marker-Based Watershed Algorithm: The marker-based watershed algorithm is a technique used for image segmentation, particularly in cases where objects in the image have distinct boundaries. In the context of brain tumor segmentation, this algorithm can help delineate the boundaries of the tumor from surrounding healthy tissue based on markers identified by the CNN. The workflow of the system involves feeding MRI images of a patient's brain into the CNN. The CNN processes the raw pixel data through convolutional, ReLU, and pooling layers to extract features relevant to tumor detection. The output is then passed through a fully connected layer for classification. After classification, the marker-based watershed algorithm is applied to generate a segmentation mask, which identifies the tumor region within the MRI image.

Overall, this approach combines the feature extraction capabilities of CNNs with the boundary delineation capabilities of the marker-based watershed algorithm to automate brain tumor segmentation in MRI images. This can potentially improve efficiency, accuracy, and consistency in tumor detection compared to manual methods.

THE DESIGN STRUCTURE OF THE COMPARATORS



RESULT ANALYSIS

Fig 1: Brain Tumor Images

Fig 2: GUI for Brain Tumour Segmentation

Fig 3: Brain Tumour Dataset Loaded

Fig 4: Dataset Preprocessing and Feature extraction

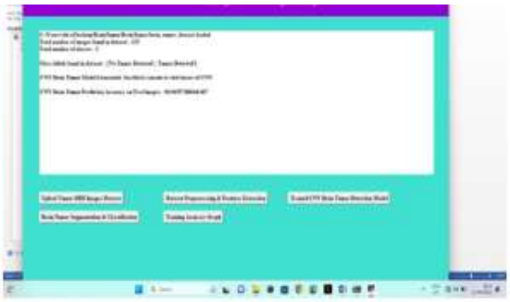


Fig 5: Trained CNN Brain Tumour Detection Model

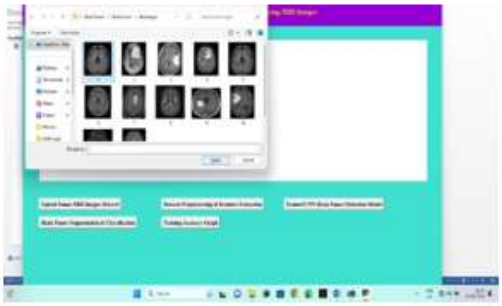


Fig 6: Selecting and Uploading No Tumour Image

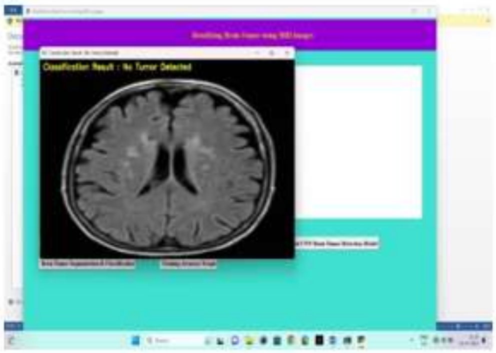


Fig 7: Result of No Tumour Image Detected

Fig 8: Selecting and Uploading Tumour Image

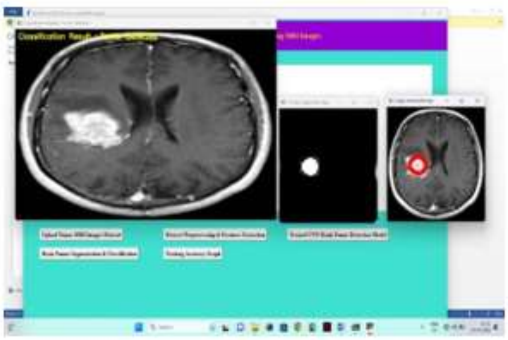


Fig 9: Result of Brain Tumour Image Detected

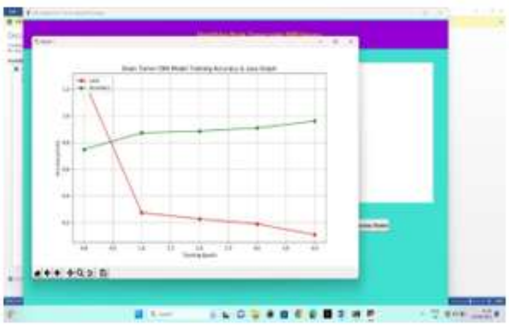


Fig 10: CNN Model Training Accuracy Graph

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CONCLUSION

In this paper, we created deep learning models based on convolutional neural networks (CNNs) and watershed algorithms to automatically segment brain tumours in MRI images. Our methodology, called "Cerebral Insight," intended to increase the accuracy and efficiency of brain tumour segmentation when compared conventional approaches. We tested several CNN architectures, regularisation techniques, and hyperparameters on the BraTS dataset to improve segmentation performance. Our findings show that deep learning is useful for automated brain tumour segmentation, reaching high accuracy while overcoming manual segmentation obstacles such as subjectivity and unpredictability. The generated models have been incorporated into a user-friendly desktop application, allowing medical practitioners to quickly apply them in clinical situations. This application provides a faster and more consistent alternative to manual segmentation, enabling improved diagnosis and treatment planning for patients with brain tumours. Overall, "Cerebral Insight" represents a cutting-edge approach to brain tumour segmentation, leveraging deep learning and advanced algorithms to enhance the analysis of MRI images and improve patient care.

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