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BRAIN TUMOR DETECTION USING DEEP LEARNING AND MRI SEGMENTATION

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Abstract
Detection of brain tumors is difficult for imaging specialists due to their high variability. Brain tumor represents an irregular growth of brain cells which may be benign or malignant [1]. Detection of brain tumor in early stages provides more treatment options. As the most appropriate tool to detect brain tumors, Magnetic Resonance Imaging (MRI) is used due to excellent soft-tissue visualization capacity [1].
However, manual analysis of MRIs by radiologists is time-consuming and requires much effort and skills. In this regard, this paper presents a solution based on a deep learning algorithm for brain tumor detection and segmentation via CNN and U-Net models [3][10].
The proposed method will improve performance in terms of brain tumor detection and segmentation. In addition, such approach will reduce the workload of specialists and improve results obtained through radiographic examination.
Keywords
Brain Tumor, MRI, Deep Learning, CNN, U-Net, Image Segmentation

1. Introduction
Brain tumor represents an irregular growth of brain tissue formed due to abnormal cell development [1][9]. It may be either benign or malignant, with malignancy representing a higher degree of risk due to spreading to other brain regions. Brain tumors need to be detected and treated as soon as possible [2].
MRI is currently among the most common methods for diagnosing brain tumors. However, radiological interpretation requires advanced training and considerable efforts. Recent advances in the field of AI gave rise to numerous deep learning techniques for solving real-world problems [8].
CNN models proved their effectiveness in tasks of medical image classification. Similarly, U-Net model was recognized for its success in image segmentation task [3][7].
The current study focuses on combining two aforementioned models for brain tumor detection and localization.

2. Literature Review
Several solutions have emerged in literature over the years to aid in identifying brain tumors using medical images. Initial techniques relied on classical machine learning algorithms such as SVM, KNN, and decision trees. Feature engineering was required in these models, whereby features were manually identified. Though reasonably accurate, the models were constrained by scalability and the dependence on human-engineered features [1].
However, the emergence of deep learning led to the use of convolutional neural networks for image recognition tasks. The CNN algorithm automatically identifies hierarchical features in images. Studies reveal that CNN algorithms outperform traditional ML models in classifying brain tumor types [7].
On the other hand, locating and demarcating brain tumors are equally essential. Classical segmentation algorithms such as thresholding, region-growing, and clustering techniques like K-

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means are commonly applied. Nevertheless, these models have difficulty identifying accurate boundaries since the tumors' shapes are irregular [5].
Recently, deep learning models, especially the U-Net [8], have received considerable attention in tumor segmentation. The network's encoder-decoder architecture enables it to identify spatial and contextual features, conducting pixel-wise categorizations. U-Net has proven highly effective in accurately marking tumor boundaries.
Notwithstanding, there are still some challenges with respect to the accuracy of the models and their ability to generalize data. Most existing models concentrate either on classification or segmentation exclusively.
The research proposal proposes a solution to this problem by integrating CNN and U-Net into one model to accomplish the task of classifying and segmenting brain tumors more accurately [3][8].

3. Problem Statement

Analysis of brain tumor images from magnetic resonance imaging (MRI) scans is complicated and demanding, and radiologists are required to carry out the process. The large number of images makes diagnosis tedious and error-prone. Incorrect identification of brain tumors can result in wrong diagnoses and delays in treatment.
Furthermore, traditional systems lack automation and have difficulties coping with variations in size, shape, and intensity of the tumors. Therefore, there is a need for an automated system to efficiently locate brain tumors.
This research will design an efficient deep learning algorithm to automate brain tumor diagnosis and localization.

4. Objective

The main goal of this project is to develop an automated tool for the Brain Tumor Detection using Deep Learning and MRI Segmentation.
Those objectives include:

- Classification of MRI images into tumor and non-tumor categories
- Reduce human effort and improve efficiency
- Locate the tumor regions accurately
- Improve segmentation accuracy using U-Net model

5. System Overview

The designed system consists of a multi layered process. In which initially, an MRI image is provided as input to the system. The Preprocessing stage ensures the image size and normalization. The image size and normalization is varied in the preprocessing stage.
Then this image passes down to the CNN model which helps in classification of MRI image into tumor and non-tumor categories. If tumor is detected, the processed image passes through trained u net model to perform segmentation and to locate the tumor region.
The Final Output of this system has the type of detected tumor, severity of the tumor, size, and height, width of tumor and location of the tumor.

6. Dataset Description

The dataset in this project consists MRI images classified as tumor and non-tumor. These images are collected from Kaggle which has publicly available medical imaging datasets. This dataset includes variety of MRI images with different tumor sizes, shapes and intensities, helps in improving the effectiveness of the model.
All uploaded MRI images are resized to 128x pixels. This process is crucial because deep learning models require specific input dimensions for efficient processing [2][3]. The dataset is further

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divided into main parts: training and testing. Where training dataset is used to train the model and testing dataset is used to evaluate unseen data.

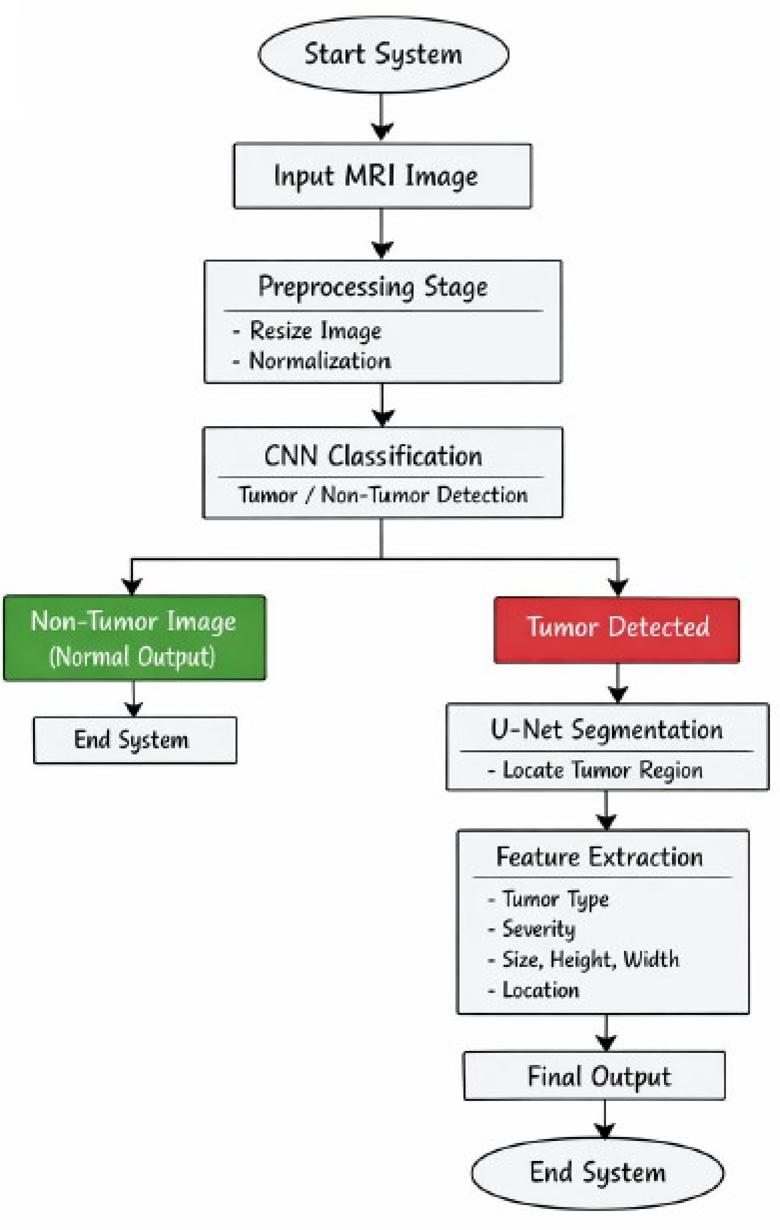

Fig.1. Block diagram illustrating the training of CNN model

7. Preprocessing

Pre-processing is an important step in preparing MRI images for input into deep learning model [10]. Raw MRI images may contain some noise, intensity variations and different sizes, which can negatively affect the performance of model. Therefore, preprocessing techniques improves data quality and certify consistency.

The initial step in preprocessing is resizing images to a fixed dimension of 128x 128 pixels. This makes sure that the model receives uniform input data. Next, normalization is done to scale pixels values from 0-255 to a range of 0-1 [4][10].

NORMALIZATION X=X/255

The processed image then converted into numerical arrays, which are given to CNN model for training. Proper preprocessing improves feature extraction and overall accuracy of the system

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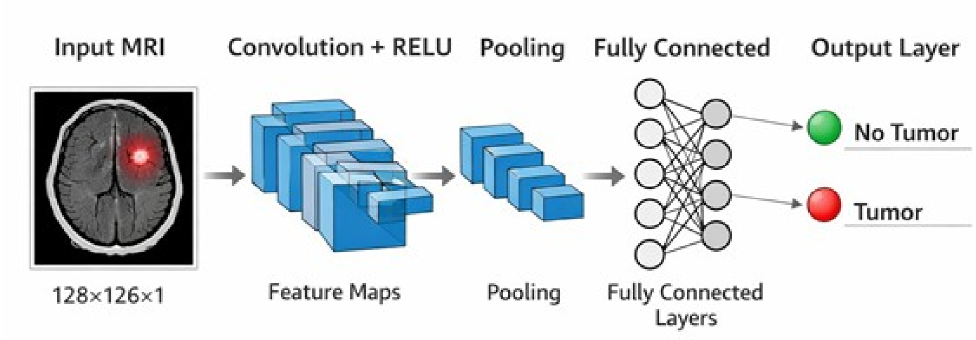

Fig.2. CNN Architecture

8. CNN Architecture

The Convolutional Neural Network (CNN) is used for classification of MRI images into tumor and non-tumor categories. CNN is a deep learning model designed for image processing task.

This CNN Architecture consists of multiple layers, they are convolutional layers, activation functions, max pooling layers and fully connected layers. These convolutional layers extract edges and patterns from the input MRI images. The ReLU activation function provides non -linearity, which allows the model to learn difficult patterns [3][7].

Max polling reduces the dimensions of feature maps, which helps in lowering computational complexity and preventing overfitting. At the end, fully connected layers does classification and a sigmoid activation that produces the output probability.

9. U-NET Architecture

U-Net is a deep learning architecture designed for biomedical image segmentation. It is mainly used in imaging applications due to its ability to perform accurate pixel-level classification. Here, U-Net is used to identify and segment the tumor region from input MRI images [8].

The architecture of U-Net consists to main blocks: The encoder and the decoder. The encoder is responsible for getting information by applying a serious of convolutional and max pooling layers. This reduces the dimensions of the image while getting features as expected.

The decoder reconstructs the image by applying upsampling operation. This gradually increases the resolution of the features to generate segmentation mask for highlighting the tumor region. The key feature of U-Net model is to skip connections that connect layers in the encoder and decoder. These connections help to save information that may be last during pooling process [8].

U-Net improves the accuracy of tumor localization and draws a bounding box around the tumor.

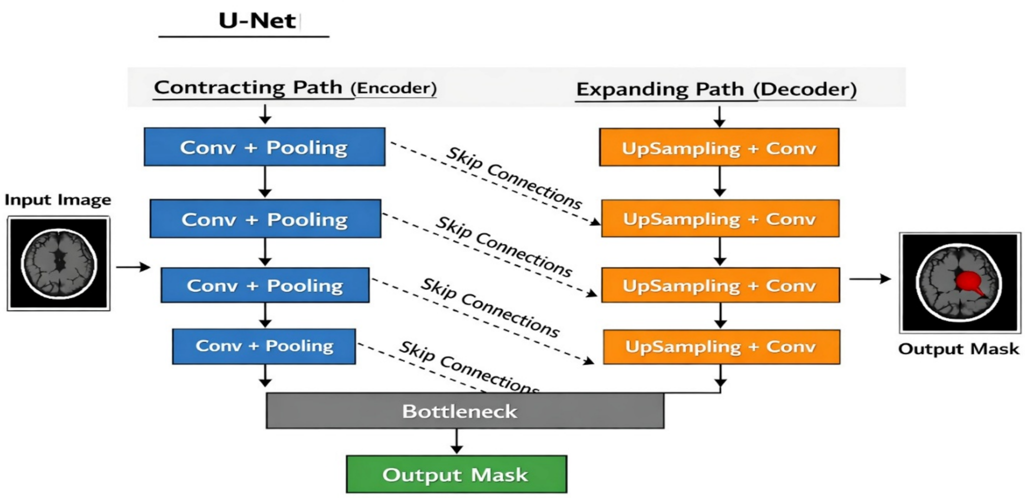

Fig.3. U-Net Architecture

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10. Mathematical Background

Working of deep learning models such as CNN and U-Net is completely based on mathematical operations like convolution, activation and pooling. The convolution operation includes sliding a filter (kernel) over the MRI images to extract the features.

Feature Map = Input Image*kernel

Activation function provides non-linearity to the model. The mostly used activation function is ReLU[6].

ReLU(x) = max(0,x)

Pooling operation decreases the size of future maps, that reduces computation complexity and preventing overfitting. Max pooling selects the maximum value from the feature map.

These operations enable the model to learn complex patterns, making it efficient for tumor detection and segmentation.

11.Training and Testing

The Training and Testing plays an important role in development of effective deep learning model.

During the Training stage, the CNN model takes the input image in batches and adjusts its internal weights using a backpropagation algorithm. The main objective is to minimize the loss and improve accuracy over multiple iterations knows as epochs.

The optimization of the parameters is carried out using Adam Optimizer, which is used for its efficiency and convergence. Learning rate, batch size and number of epochs are carefully selected to get optimal performance. Data augmentation increases diversity of datasets by applying rotation, flipping and scaling.

After training, the model is tested using the testing dataset. The performance is measured such as accuracy and precision. These evaluation metrics gives insights into how the model performs in detecting tumors.

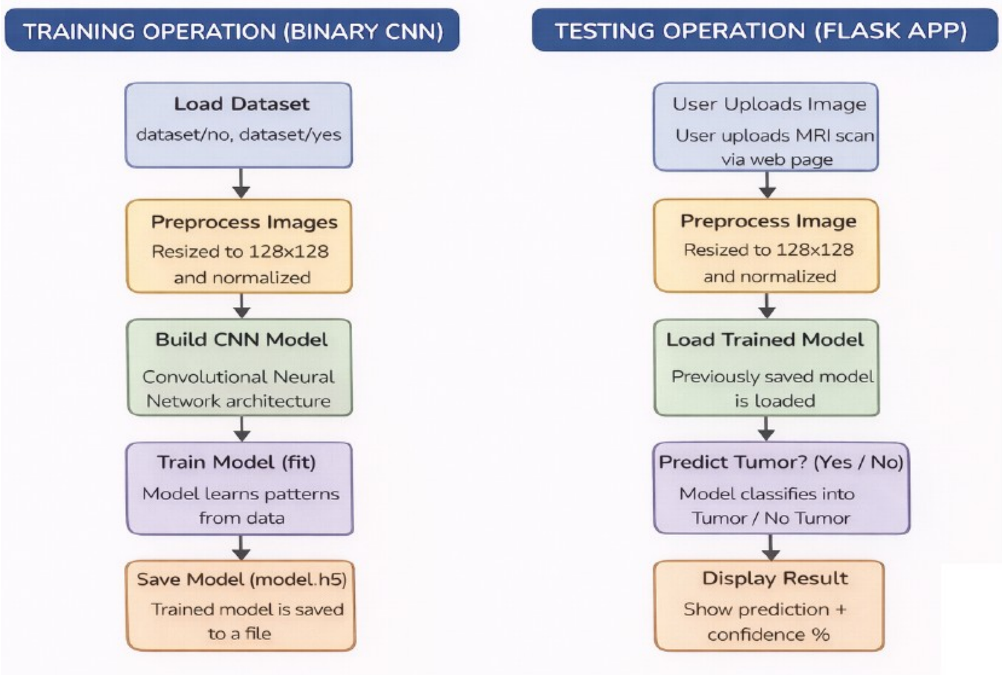

Fig.4. Path Flow of Training and Testing Operations

12. Prediction Logic

After the model gets trained, it is used to detect tumors in new MRI images. The CNN model gives a probability value between 0 and 1 that indicates the presence of tumor.

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A threshold value of 0.4 is used for classification if the predicted value by CNN model is greater than 0.4, the MRI image contains tumor. If the predicted value is less than or equal to 0.4, it contains no tumor.
This logic makes sure that the project provides classification and also measures the reliability, which is most important in medical field.

13. Tumor Detection and Localization

Tumor detection and locating it are the features of proposed system; they provide visual identification of the tumor in MRI images. Localization provides exact position and boundaries of the tumor, this makes medical diagnosis and treatment planning easier.
Two approaches are used for tumor detection and localization in this project: Open CV – based methods and deep learning-based segmentation using U-Net model. First, the uploaded MRI image is converted into grey scale [6][7]. Then, thresholding is applied to identify the tumor region based on intensity differences.
After thresholding, a bounding box is drawn around this region to highlight the tumor. Even this model is simple, it may not always provide exact boundaries for the detected tumor.
A U-Net based segmentation is used to overcome these limitations. U-Net allows the model to identify the precise shape and size of the tumor. It generates a segmentation mask, providing more efficient localization.
The combination OpenCV and U-Net ensures fast detection and more accuracy. This combinational approach is more effective for real-world applications.

14. Performance Evaluation Metrics

The performance of the proposed is evaluated by using some evaluation metrics. These provide a measure of how the model performance in detection.
Accuracy is the measure of correctly predicted instances. It gives an idea about model performance.
Precision gives the proportion of correctly predicted tumor images out of all predicted cases. It shows how reliable the model is. These metrics provide the performance measure of the model in real-world medical scenario.

15. Result and Discussions

This deep-learning based system for brain tumor detection is evaluated using MRI images from the dataset. The result tells that system is capable of providing effective localization of tumor regions and accurate classification.
The combination of CNN and U-Net models ensures classification and precise localization to make the system more effective for medical applications [6][8].

Table 1. Comparison of Proposed Method with Existing Techniques

S. No.	Method	Technique used	Accuracy	Description
1	Traditional Methods	Thresholding	75-85%	Low Accuracy
2	Machine Learning Models	SVM, KNN	80-88%	Requires Manual Feature Extraction
3	CNN Model	Deep-Learning (Classification)	90-92%	No tumor localization
4	U-Net Model	Deep-Learning (Segmentation)	94-97%	Higher cost
5	Proposed System	CNN+U-Net	97-99%	Improved Accuracy and Localization

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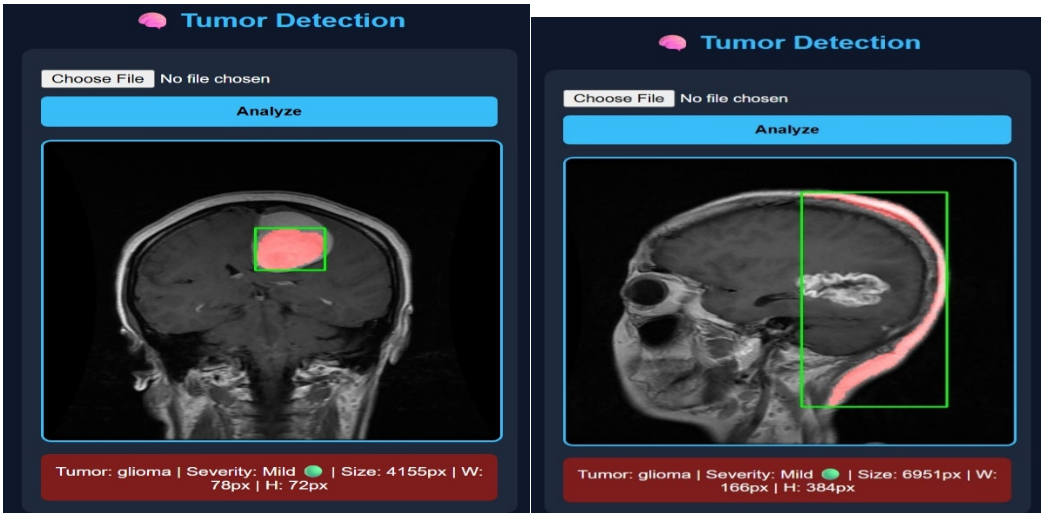

Fig.5. Illustration of Results with different MRI images

16. Advantages of the Proposed System

This proposed system has few advantages over the existing systems such as Traditional methods, machine learning methods, individual CNN and U-Net models. One of those advantages is automation, which reduces the need of manual analysis of the radiologists. By using deep-learning models, the system process MRI images efficiently saving the valuable time in medical analysis.

In addition, the pre-processing techniques increase the quality of input data, leading to better model performance. This designed system is scalable as it is extendable to use larger datasets for real-time applications.

The ability to highlight tumor regions makes the system more interpretable and user friendly.

17. Conclusion

In this project, a deep-learning based system for brain tumor detection and segmentation using MRI images is been presented. The system combines both Convolutional Neural Network (CNN) and U-Net models to achieve accurate classification and tumor localization.

The CNN model extract features from the MRI images and classifies them into tumor and non-tumor categories. This uses the pre-processing techniques that involve resizing the image and normalization. The integration of U-Net architecture provides pixel level segmentation allowing for precise localization of the tumor.

The results demonstrate that the proposed system overcomes the limitations of traditional methods by providing accurate detection. The capability to locate the tumor regions makes the system more useful for medical professionals. In addition, it reduces the workload on the radiologists and faster analysis of MRI images.

Overall, the combination of CNN and U-Net models makes the system efficient, reliable and accurate for classification and localization of the tumor which is perfect for the real-world applications.

18. Future Scope

Even this system provides promising results, there are several areas of improvement is the use of attention U-Net and U-Net++, which can further improve accuracy in segmentation. That also helps in improving performance, especially when working with limited number of datasets.

The system can be extended to support real-time integration with hospital management systems. The combination of CNN and U-Net models helps in accurate classification and localization that can save more time and reduce workload for radiologists.

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