Brain Tumor Detection Using CNN

1 Introduction

Medical imaging is a non-invasive technique used for diagnosing and treating various health conditions. Among its applications, image segmentation plays a crucial role in analyzing medical images, especially for detecting tumors and lesions. Accurate segmentation helps in early diagnosis and improves treatment outcomes.

Brain tumors, which can be malignant or benign, pose serious health risks. Malignant tumors grow aggressively and may spread to other parts of the brain, while benign tumors grow slowly but can still affect brain function. According to the World Health Organization (WHO), around 400,000 people worldwide are affected by brain tumors, with a significant number of fatalities each year. Early detection is essential for improving survival rates.

Magnetic Resonance Imaging (MRI) is widely used for brain tumor detection, but manually segmenting tumors from MRI scans is time-consuming and complex. This process requires analyzing a large number of images, and the tumors often have unclear boundaries. To address these challenges, an automated method based on both traditional classifiers and Convolutional Neural Networks (CNNs) is proposed. This approach enhances accuracy and efficiency in tumor segmentation and detection, reducing the need for manual intervention.

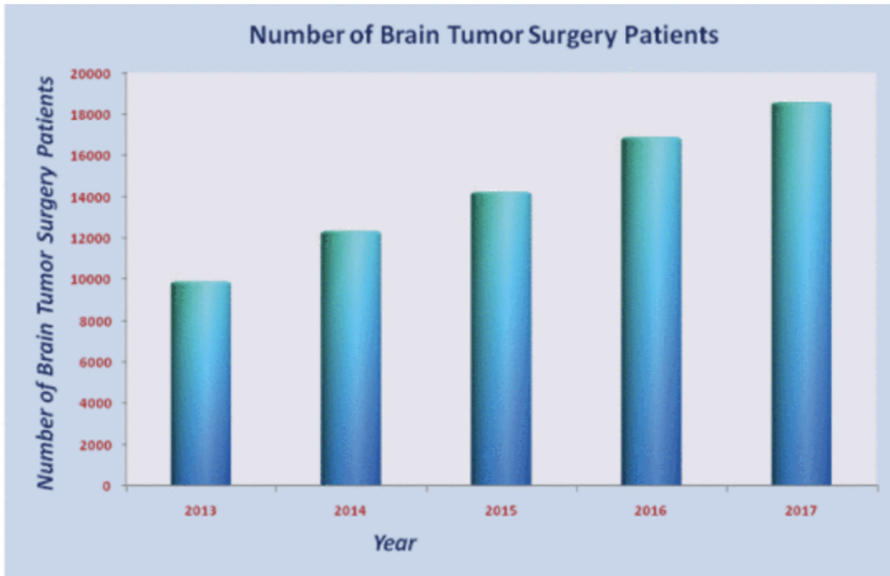

Figure 1: No of Brain Tumor Surgery in India

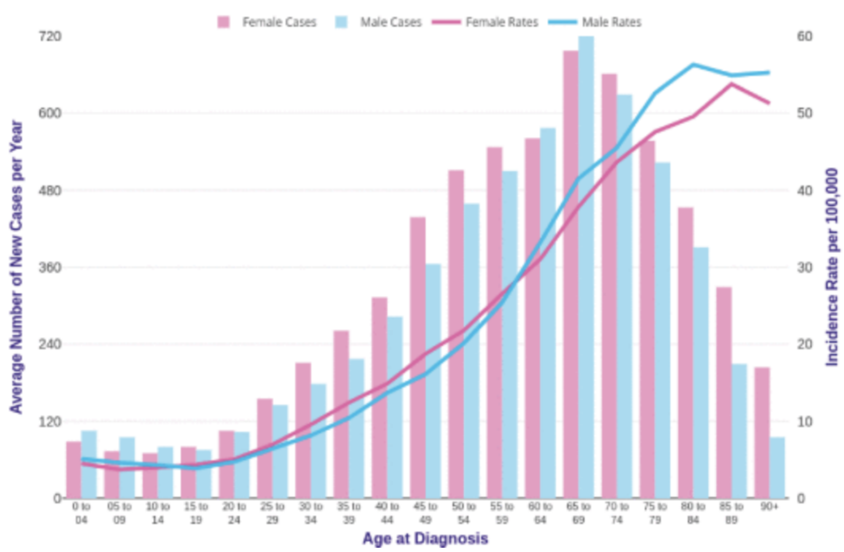

Figure 2: Average Number of New Cases per Year and Age-Specific Incidence

2 Literature Review

Segmenting tumors from MRI brain images is a complex task, with various approaches explored to improve accuracy and efficiency. Mathematical Morphological Operations and spatial clustering techniques have been used for tumor detection, achieving high classification accuracy. Histogram-based segmentation, active contour models, and k-means clustering have also shown promising results. Edge detection methods, such as Canny edge detection with adaptive thresholding, have been compared for segmentation accuracy.

Tumor growth patterns, label maps, and probabilistic neural networks have been applied to enhance segmentation and classification. Feature extraction techniques like PCA, combined with machine learning models, have improved classification performance. Enhanced clustering models and deep learning architectures, such as LinkNet, have demonstrated significant improvements in segmentation accuracy. Neural networks and machine learning-based methods continue to advance tumor detection by improving accuracy and reducing processing time.

3 Methodology

A Convolutional Neural Network (CNN) model is employed for brain tumor detection using MRI images. The process begins with brain region extraction, followed by tumor segmentation. The segmented regions are then analyzed by the CNN to classify tumors into different categories.

The CNN-based classification system operates in two main stages: training and evaluation. During training, MRI images are labeled into four categories: glioma, meningioma, pituitary tumor, and no tumor. The process involves three key steps: preprocessing, feature extraction, and classification.

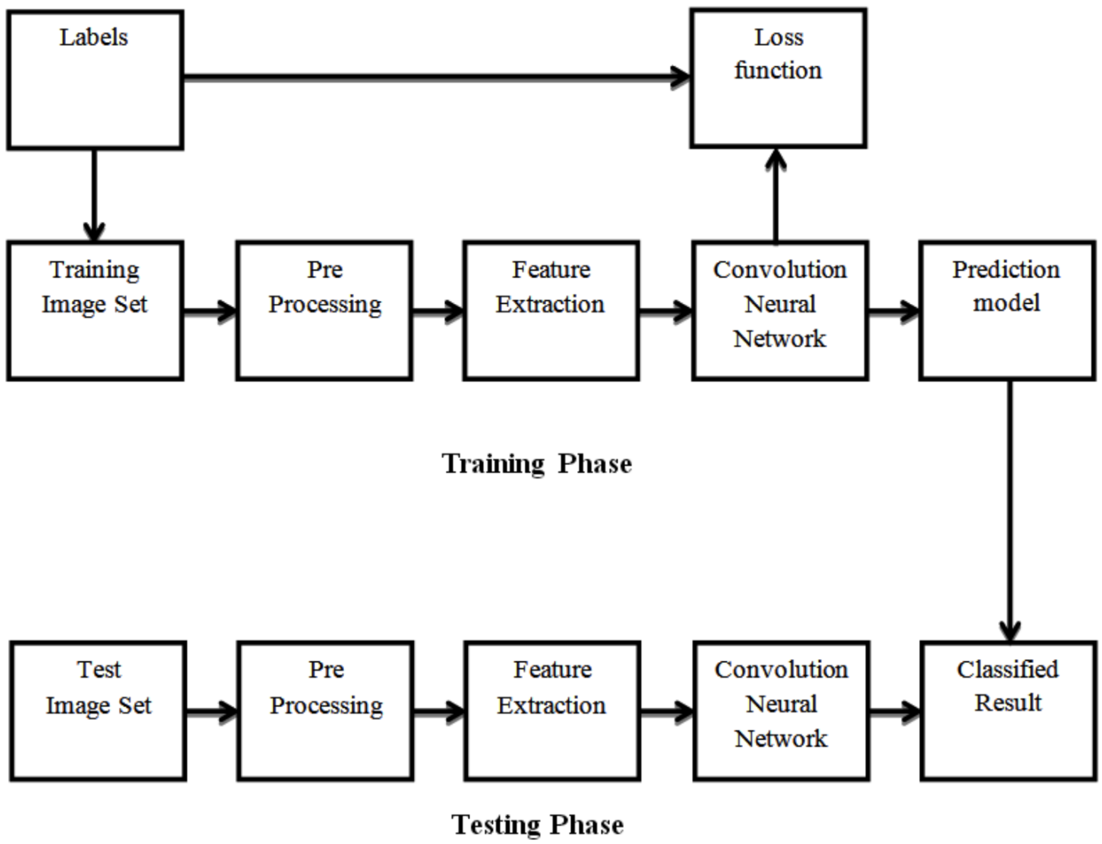

Figure 3: Block diagram of proposed brain tumor classification using CNN

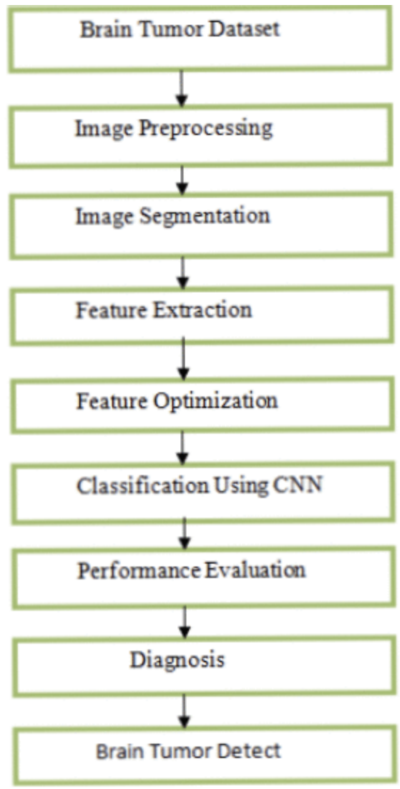

Figure 4

3.1 Dataset Source

The model is trained on a publicly available brain MRI dataset from Kaggle:

- **Dataset Source**: `https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset`
- **Description**: The dataset used for brain tumor classification consists of MRI scans categorized into four classes: *glioma*, *meningioma*, *pituitary*, and *no tumor*. It is structured into two main subsets:
  - **Training Set:** Contains labeled MRI images for model training, helping the classifier learn distinct features of each tumor type.
  - **Testing Set:** Includes separate MRI images used to evaluate the model's performance on unseen data.

  Each subset is further divided into four categories based on tumor type, ensuring a well-organized dataset suitable for supervised learning.

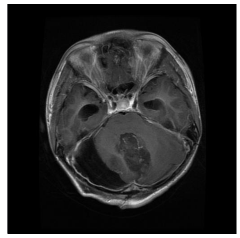

Figure 5: glioma

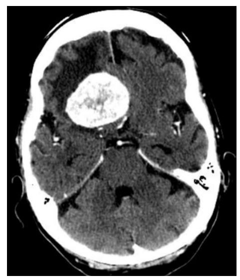

Figure 6: meningioma

Figure 7: no tumor

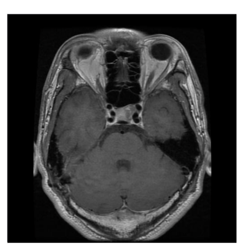

Figure 8: pituitary

3.2 Image Preprocessing

Before training, the MRI images undergo preprocessing to enhance quality and improve classification accuracy. The key steps include:

- **Resizing**: All images are resized to a fixed dimension for uniformity.
- **Grayscale Conversion**: Converts images to grayscale to reduce complexity.
- **Normalization**: Pixel values are scaled between 0 and 1 to speed up learning.
- **Augmentation**: Techniques like rotation, flipping, and zooming are applied to increase dataset diversity.
- **Noise Removal**: Filters are used to smooth images and remove unwanted noise.

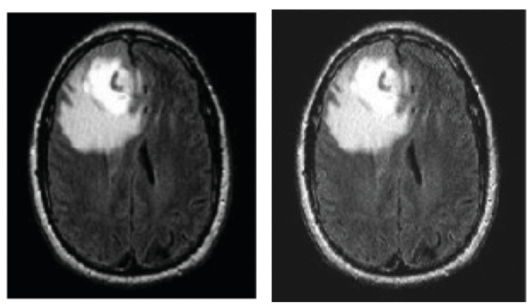

Figure 9: Raw Image and Preprocessed Image

3.3 Image Segmentation

Image segmentation is the process of dividing an image into regions based on differences in shades, textures, brightness, contrast, and gray levels. A digital grayscale image is used as input, and anomalies are identified as output. The goal of segmentation in medical imaging is to extract meaningful data from images for better analysis. Various techniques, such as Neural Networks, Decision Trees, Rule-Based Algorithms, and Bayesian Networks, are used to improve segmentation accuracy.

Common segmentation methods include:

- **Thresholding Method**: Voxels above a certain threshold are classified as tumor regions.
- **Region Growing Method**: A seed voxel is selected, and similar surrounding voxels are grouped as part of the tumor.
- **Edge Detection Method**: Changes in density between voxel edges are identified as tumor boundaries.

3.4 Feature Selection

Feature extraction is the process of capturing the visual content of an image by transforming raw data into a more meaningful representation. It reduces the image complexity while preserving essential information for decision-making, such as pattern classification. After brain segmentation, Discrete Wavelet Transform (DWT) is used to further process MRI images. The DWT method utilizes a combination of low-pass and high-pass filters to extract key features.

3.5 Image Classification

Image classification involves labeling images based on their characteristics. The most effective classification function is determined using Genetic Algorithms (GA) and other optimization techniques. Additionally, GA is integrated with multiple classifiers, such as Convolutional Neural Networks (CNN) and Machine Learning (ML) models, to enhance performance.

3.6 Feature Optimization

Feature optimization combines feature selection and extraction, playing a crucial role in brain image processing. Feature selection reduces the dimensionality of the dataset, improving computational efficiency and reducing processing time for accurate tumor detection.

3.7 Convolutional Neural Network Architecture

In medical image processing, neural networks are widely used for tumor detection. Over the years, researchers have worked on improving models to enhance accuracy. To evaluate the proposed brain tumor classification system, training accuracy, validation accuracy, and validation loss are measured.

A fully connected neural network can identify tumors, but CNN is preferred due to parameter sharing and connection sparsity. CNN has a hierarchical structure with multiple layers, including convolutional, pooling, normalization, and fully connected layers.

3.7.1 Convolutional Layer

CNN is commonly used for image recognition and classification. It processes input images by converting them into pixel arrays and applying filters to extract features. The convolution operation helps identify spatial dependencies within the image.

3.7.2 ReLU Activation

The Rectified Linear Unit (ReLU) introduces non-linearity by converting negative pixel values to zero. It improves training efficiency and helps the network learn complex patterns.

3.7.3 Pooling (Downsampling)

Pooling reduces the dimensionality of feature maps while retaining important information. Common pooling methods include max pooling, average pooling, and sum pooling. Max pooling selects the highest value from a region, reducing computational complexity and preventing overfitting.

3.7.4 Fully Connected Layer

This layer takes the output of previous layers, flattens it, and converts it into a single vector. It enables classification by mapping extracted features to output labels. CNN-based models are trained on large datasets to improve tumor detection accuracy.

4 Model Architecture

The model is built using a **Sequential** structure, consisting of multiple layers. It includes **Conv2D** layers for feature extraction, followed by **MaxPooling2D** layers to reduce spatial dimensions. A **Flatten** layer converts the feature maps into a one-dimensional vector, which is then passed through two **Dense** (fully connected) layers. A **Dropout** layer is added to prevent overfitting.

- **ReLU activation** is used in the convolutional layers for non-linearity.
- **Softmax activation** in the final dense layer outputs class probabilities.
- **Adam optimizer** is used for efficient learning.
- **Categorical cross-entropy** is the loss function, as this is a multi-class classification problem.
- **Accuracy** is tracked as the performance metric during training.

5 Model Training

- Implemented a CNN from scratch using TensorFlow and Keras.
- Trained using Adam optimizer and learning rate scheduling.
- Used dropout and batch normalization to prevent overfitting.

6 Conclusion and Future Work

Brain tumor detection relies on accurate image segmentation, with MRI being the most effective modality. In this work, we applied Fuzzy C-Means clustering for tumor segmentation and classified tumors using traditional classifiers and CNNs. Among traditional classifiers, SVM achieved the highest accuracy of 92.42

CNN methods are best for the accuracy level with a lower rate of error. So the target region is segmented and the determination of the existence of the tumor using the technique proposed here lets doctors make the treatment plan and condition of the tumor surveillance in the diagnosis. The benefits of this method are it increases the segmentation level and spatial localization of the image and thus improves the performance relative to the other system. It takes less time to compute and is faster to train than other networks with fewer parameters. The accuracy method is most arise using CNN. In this future work like improving the accuracy with a low rate of error using different classifier techniques.

In the future, we aim to explore 3D brain imaging, work with larger datasets, and develop a region-specific dataset to improve diagnostic precision.

References

[1] J. Seetha and S. Selvakumar Raja, "Brain Tumor Classification Using Convolutional Neural Networks," *Biosciences Biotechnology Research Asia*, vol. 15, no. 1, 2018. Available: `http://dx.doi.org/10.13005/bpj/1511`

[2] T. Hossain, F. S. Shishir, M. Ashraf, M. A. A. Nasim, and F. Muhammad Sha, "Brain Tumor Detection Using Convolutional Neural Network," in *Proc. Int. Conf. on Advances in Science, Engineering and Robotics Technology (ICASERT)*, 2019. DOI: `10.1109/ICASERT.2019.8934561`