

Brain Tumor Detection System Using CNN with Alexnet Extraction

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ABSTRACT

The Brain Tumor Detection, localization, and area calculation system serves as a hybrid AI-based diagnostic framework that integrates deep learning with classical image processing techniques to improve brain MRI analysis. The system automates tumor detection, reducing manual effort and improving accuracy and consistency at the initial stage, MRI scans are classified as tumor-positive or tumor-negative using Alex Net, a pre-trained convolutional neural network fine-tuned on brain MRI data. The steps serve as a filter, ensuring that only relevant images proceed to further analysis. The subsequent stage involves skull stripping to isolate brain tissue from surrounding structures. Otsu's is applied to adaptive thresholding, followed by morphological operations to improve the quality of the brain mask and eliminate non-brain artifacts. Next, tumor region is performed using a multi-thresholding approach to manage MRI intensity variations. Morphological smoothing and connected component analysis was used to remove noise and accurately define tumor boundaries. The proposed system localizes and quantifies the tumor by calculating its centroid and area as a percentage of total brain volume. Additional shape and texture features support tumor characterization. The results are presented in an interactive report with annotated images and numerical summaries, making the system efficient, reliable, and applicable for hospital deployment.

KEYWORDS:

Convolutional Neural Network (CNNs), MRI (Magnetic Resonance Imaging), Centroid, AlexNet.

I . INTRODUCTION:

Brain tumors are one of the most severe and life-threatening neurological disorders, and early detection is crucial for improving patient survival rates. As reported by the World Health Organization (WHO), brain tumors account for approximately 2% of all cancer-related deaths. Their diagnosis primarily relies on Magnetic Resonance Imaging (MRI) due to its superior soft-tissue contrast and non-invasive nature. However, manual interpretation of MRI scans by radiologists is time-consuming, subjective, as well as prone to error especially when tumors are small, irregularly shaped, or located in complex brain regions. Misdiagnosis or delayed diagnosis may result in inappropriate treatment plans and increase morbidity patient outcomes.

To address these challenges, this project proposes an automated Brain Tumor Detection, Localization, and Area Calculation System that integrates deep learning (Alex Net) with advanced image processing techniques. The system was designed to mimic and enhance the diagnostic capabilities of radiologists by delivering fast, accurate, and reproducible tumor analysis. Unlike conventional manual approaches that depend solely on visual inspection, the proposed framework automates the entire diagnostic pipeline, thereby reducing human intervention while improving precision.

II . ARCHITECTURE OF CONVOLUTIONAL NEURAL NETWORK

It is a deep learning algorithm specifically developed to process and analyze visual data (for example: images, videos, and patterns). This represents a kind of artificial neural network that automatically extracts important features from images without involving manual feature extraction. The CNN architecture mimics the visual processing of the human brain, enabling it to identify shapes, edges, textures, and objects within an image.

The network obtains an image as input, functions it through multiple layers, and produces an output that classifies the image into a particular category or detects specific objects. CNN's are widely used in applications such as image categorization, medical image diagnosis, face identification, and object detection due to their high accuracy and efficiency.

The CNN algorithm operates through a sequence of well-structured layers, each performing a particular function. The

beginning stage is the convolutional layer, which applies a lay of filters (kernels) to the input image to extract important features such as edges, lines, and corners. Each filter slides across the image and produce an feature map that highlights specific qualities.

Next, an activation function commonly the Rectified Linear Unit (Rel U) is applied to introduce non-linearity into the model by fixing negative values to zero. This step allows the network to learn complex and abstract patterns.

After activation, a pooling layer decreases the dimensional of the feature maps while retaining the most important information. Pooling improves computational efficiency and helps to prevent over fitting by generalizing the learned features.

Once the features are extracted and reduced, the data is flattened into a one- dimensional vector and passed into one or more fully connected (dense) layers. These layers combine the extracted features to make the final decision or classification. The output layer uses an activation function such as Soft max or Sigmoid, depending on whether the problem is multi-class or binary classification.

For example, In medical imaging tasks like brain tumor detection, CNN's analyze MRI scans and classify regions as tumor or non-tumor by learning complex tissue patterns and abnormalities.

The all network was trained using a function called back propagation, where errors are minimized by adjusting the filter weights through gradient descent. Thus the architecture of convolutional neural network (CNN) can be shown in the figure 1.

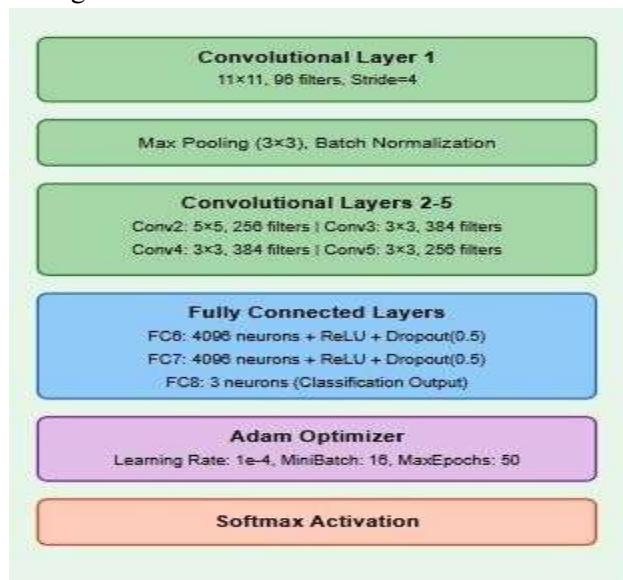


Fig 1. Architecture of CNN Module

III . PROPOSED WORK

The proposed system initiate the automated framework for brain tumor detection and analysis by integrating deep learning and advanced image processing proficiency. Traditional diagnostic approaches rely on manual interpretation of Magnetic Resonance Imaging (MRI) scans, which are time-consuming and dependent on inter-observer variability.

To address these limitations, the proposed work employs a four-stage of pipeline consist classification, skull stripping, tumor segmentation, and anatomical localization with quantitative analysis. The system combines the feature extraction capability of Alex Net with robust segmentation algorithms to achieve high accuracy while maintaining computational efficiency suitable for medical applications.

➤ Deep Learning-Based Classification

The Network Architecture is based on Alex Net, which comprises five convolutional layers followed by three fully connected layers. The first convolutional layer applies 11×11 kernels for capturing global spatial features, while subsequent layers work as 5×5 and 3×3 filters to extract fine-grained patterns. Max-pooling layers decrease spatial dimensions and retain dominant features.

Rectified Linear Unit (ReLU) activation functions are utilize developed training convergence. Local Response Normalization improves generalization, and dropout layers mitigate over fitting. This architecture enables hierarchical feature learning suitable for medical image analysis.

➤ **Skull Stripping and Otsu Thresholding**

Skull stripping was developed by Otsu’s thresholding method, which determines the optimal threshold by minimizing intra-class variance and maximizing the inter-class variance. This approach effectively separates brain tissue from background structures in T1-weighted MRI images.

➤ **Morphological Refinement**

Morphological opening was applied to remove small artifacts, while closing operations filled minor holes within the brain region. Connected component analysis retained the largest contiguous region corresponding to brain tissue, resulting in a refined brain mask.

➤ **Tumor Segmentation**

A . Multi-Threshold Segmentation

To handle tumor heterogeneity, an adaptive multi-threshold approach was used. Three thresholds were computed based on intensity histogram analysis to separate cerebrovascular fluid, normal tissue, and hyper intense tumor regions. This method improves segmentation robustness across varying MRI intensity distributions. **B . Watershed Transform**

A marker-controlled watershed transform was employed to refine tumor boundaries. and gradient magnitude image was generated to detect edges, and regional maxima were used as markers. This approach reduces over-segmentation and ensures anatomically consistent tumor delineation.

➤ **Anatomical Localization and Quantitative Analysis**

A. Lobe Localization

Tumor localization was performed using standardized coordinate systems such as Tracheal space and the Montreal Neurological Institute (MNI) space. The tumor centroid was mapped to one of the major brain lobes (frontal, temporal, parietal). For multi-lobar tumors, percentage lobe involvement was calculated.

B. Tumor Quantification

Tumor area was calculated in square millimeters using pixel resolution parameters. Relative tumor burden was expressed as a percentage of intracranial volume. For longitudinal analysis, volumetric changes were calculated across sequential scans. Confidence intervals were included to indicate segmentation reliability.

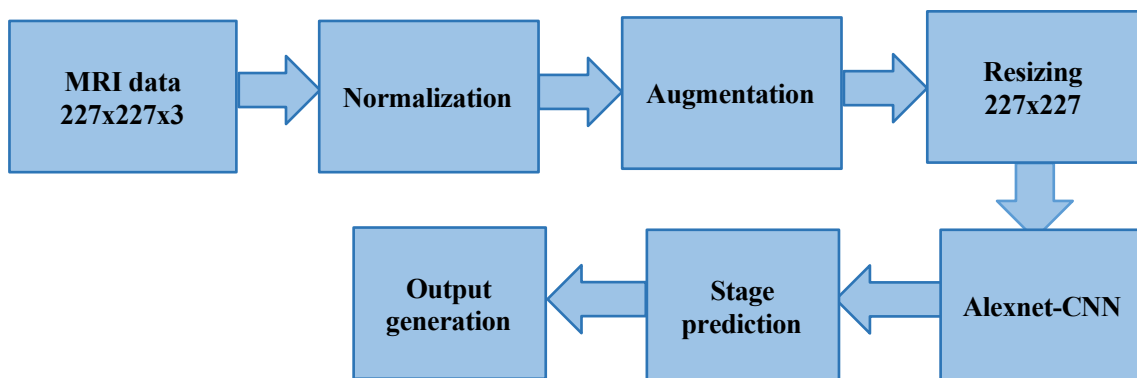


Fig 2 Block diagram of proposed system

IV. SOFTWARE REQUIREMENTS

Software Requirements:

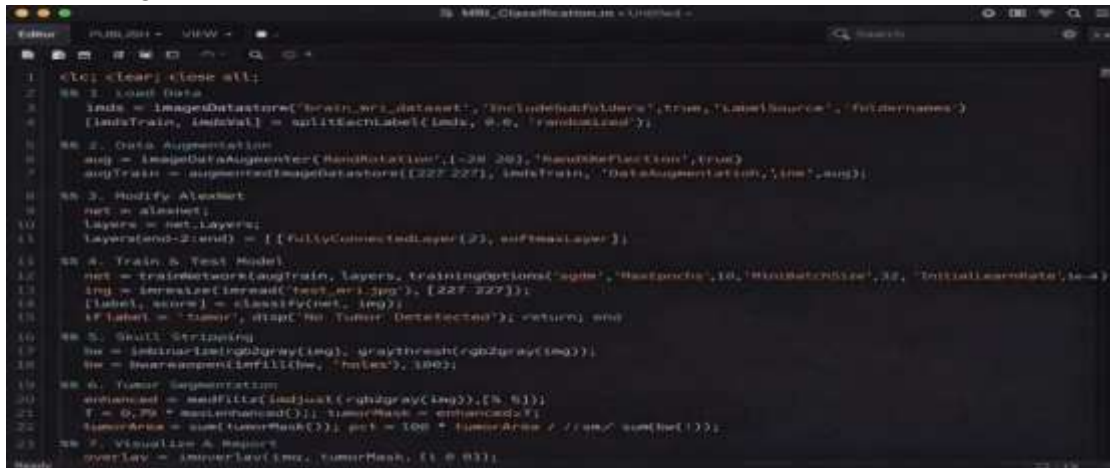
Operating System: Windows 8 / Linux

Software package:MATLAB R2014a

Language:Front end - MATLAB, Back end - C , C++

4.1. SIMULATION TOOL AND MATLAB IMPLEMENTATION

MATLAB (Matrix Laboratory) is a high-performance computing environment widely used in medical image processing, deep learning, and algorithm development. Its Image Processing Toolbox, Deep Learning Toolbox, and Computer Vision Toolbox provide optimized functions for brain tumor detection, segmentation, and analysis. are shown in fig 3.



```
1 <clear> <close> close all;
2 % 1. Load Data
3 inds = imageDatastore('brain_mri_dataset', 'IncludeSubfolders', true, 'LabelSource', 'FolderNames');
4 [indsTrain, indsVal] = splitEachLabel(inds, 0.8, 'randomized');
5
6 % 2. Data Augmentation
7 aug = imageDataAugmenter('RandRotate', [-20 20], 'RandShearFactor', true);
8 indTrain = augmentedImageDatastore([227 227], indsTrain, 'DataAugmentation', 'aug');
9
10 % 3. Modify AlexNet
11 net = alexnet;
12 layers = net.Layers;
13 layers(end-2:end) = [FullyConnectedLayer(2), softmaxLayer];
14
15 % 4. Train & Test Model
16 net = trainNetwork(indTrain, layers, trainingOptions('sgd', 'MaxEpochs', 10, 'MiniBatchSize', 32, 'InitialLearnRate', 0.01));
17 img = imread('img1.jpg', [227 227]);
18 [label, score] = classify(net, img);
19 if label == 'tumor', disp('No Tumor Detected'); return; end
20
21 % 5. SKULL STRIPPING
22 img = imresize(img, [227 227]);
23 img = imopen(imfillbw, 'holes', 100);
24
25 % 6. Tumor Segmentation
26 enhanced = imfillz(imjzact(rgb2gray(img)), [5, 5]);
27 T = 0.75 * max(enhanced(:)); tumorMask = enhanced > T;
28 tumorArea = sum(tumorMask(:)); pct = 100 * tumorArea / sum(img(:));
29
30 % 7. Visualize & Report
31 overlay = imoverlay(img, tumorMask, [1 0 0]);
```

Fig 3 MATLAB implementation

V. EXPERIMENTAL RESULTS

A . MR Image with Tumor Region

The original MR image is displayed with the suspected tumor region highlighted using a rectangular bounding box. The highlighted area represents the abnormal hyper-intense region detected in the left hemisphere of the brain. The localization is performed after preprocessing steps such as skull stripping, filtering, and segmentation. Input data of proposed system are shown in fig 4.

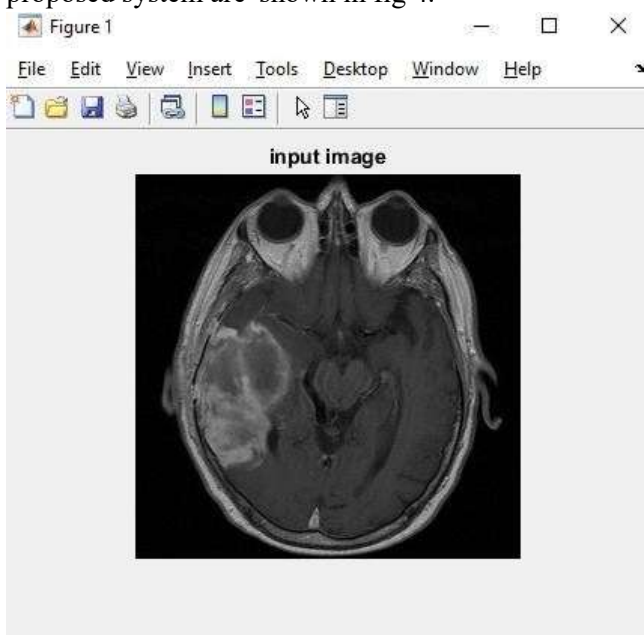


Fig 4 Input data of proposed system

B. Scanned Image with Boundary Detection

The scanned image shows the outer boundary of the brain marked using contour detection. A vertical mid line is drawn to divide the brain into left and right hemispheres for asymmetry analysis.

➤ Score Plot for Vertical Direction

- The vertical score plot represents the intensity variation along the vertical axis of the MRI image.
- Peak point (marked in red) indicates maximum intensity variation.
- Lowest point (marked in magenta) represents minimum intensity response.

➤ Score Plot for Horizontal Direction

- The horizontal score plot shows intensity variation across the horizontal axis.
- Green point indicates a significant positive intensity change.
- Blue point represents a strong negative deviation.
- Sharp drop in the curve confirms asymmetry caused by tumor growth.

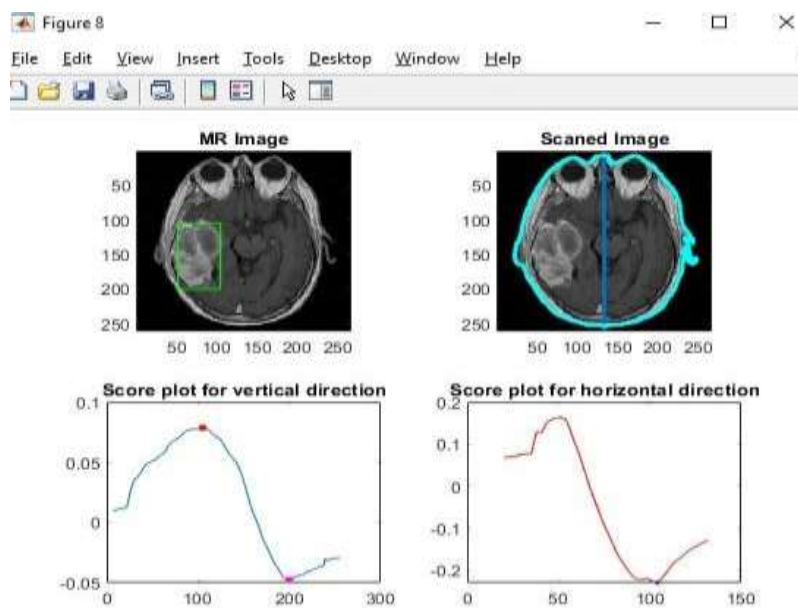


Fig 5 shows the output of Proposed system

VI. CONCLUSION AND FUTURE SCOPE

The proposed deep learning-based system for multi-classification of brain tumor images demonstrates high accuracy and reliability in distinguishing between different tumor types such as glioma, meningitis, and pituitary tumors. By leveraging deep neural network architectures, particularly transfer learning with Efficient Net, the model effectively extracts rich and discriminate features from MRI scans, leading to improved classification performance compared to conventional machine learning approaches.

The experimental results show that the model achieves strong classification across multiple tumor classes, even under varying imaging conditions. The integration of data augmentation, class balancing, and fine-tuning strategies ensures robust learning and reduces over fitting, while Grad-CAM visualizations enhance model interpretability by highlighting the critical tumor regions influencing predictions.

Overall, this work confirms that deep neural networks can significantly enhance automated brain tumor diagnosis,

aiding radiologists in early detection and decision-making. Future improvements may include the use of 3D volumetric data, hybrid ensemble architectures, and larger annotated datasets to further increase diagnostic precision and clinical application.

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