# Automated Detection of Brain Tumors in MRI Images Using Image Processing Techniques

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**Abstract:** Tumors are currently the second leading cause of cancer-related deaths, posing a serious threat to numerous patients worldwide. The medical field urgently needs efficient, automated, and reliable techniques for tumor detection, particularly for brain tumors. Early and precise identification is essential for effective treatment, as it enables healthcare professionals to mitigate further complications and manage patient outcomes more successfully. Various image processing methods have been developed to support physicians in providing accurate diagnoses and life-saving treatments. However, manually segmenting brain tumors from MRI scans is a challenging, labor-intensive, and error-prone process. Accurate and dependable tumor segmentation is crucial for diagnosis, treatment planning, and monitoring therapeutic outcomes. Most automated brain tumor segmentation approaches rely on manually designed features, while traditional deep learning models like CNNs often require extensive annotated medical datasets for training, which are challenging to acquire. This study introduces a novel two-pathway-group CNN architecture for brain tumor segmentation, which captures both local and global contextual features to address the limitations of traditional techniques. The bidirectional equivalence within the model reduces instability and prevents overfitting. Additionally, the proposed cascaded design incorporates a two-way multicast CNN structure, where outputs from the base CNN serve as auxiliary data, merged at the final stage. Testing on the BRATS2013 and BRATS2015 datasets reveals that this architecture enhances performance over existing state-of-the-art methods while remaining computationally efficient.

Keywords: CNN, MRI, BRATS, ANN, Pre-Processing

## I. INTRODUCTION

Brain tumors are among the most severe health conditions, affecting millions of people worldwide. These tumors arise due to abnormal brain cell properties and typically progress through two stages: primary and secondary. In the primary stage, tumors are smaller and categorized as "benign." In contrast, secondary-stage tumors grow larger and spread to other body parts, earning the "malignant" classification. According to the National Brain Tumor Society in the United States, approximately 700,000 individuals are affected by brain tumors. Of these, 69.8% are benign, while the remainder are malignant. Alarmingly, only 36% of patients with malignant brain tumors survive. The number of cases rose from 84,170 in 2020 to 87,000 in 2021, with most cases (69,950) occurring in individuals over 40 years of age. Brain tumors are further divided into High-Grade Glioma (HGG) and Low-Grade Glioma (LGG), with HGG having a significantly lower survival rate than LGG. The prognosis of brain tumor patients largely depends on timely and accurate treatment. In the primary stage, radiographic techniques often help patients avoid surgery. In the secondary stage, radiography and chemotherapy are commonly employed for treatment. Accurate early diagnosis plays a crucial role in treatment planning. Modern medical practices rely heavily on imaging technologies for diagnosing and categorizing cancers, including brain, skin, stomach, and blood cancers. For brain tumor classification, imaging methods like Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) are widely used, with studies showing that MRI provides superior results compared to CT scans. In recent years, Computer-Aided Diagnostic (CAD) systems have gained popularity in automating the early detection and classification of brain tumors, enabling more effective intervention and improved outcomes for patients.

Tumors can have a profound impact on the brain, destroying cells in the affected region and potentially leading to brain function. The severity of the tumor's effects largely depends on its size and location within the brain. Deep learning has shown exceptional capabilities in detecting diseases using medical imaging techniques such as X-rays, MRI scans, and CT scans, significantly enhancing the speed and accuracy of diagnoses. Brain tumors are typically identified and diagnosed through detailed medical procedures, with Magnetic Resonance Imaging (MRI) being one of the most commonly used methods. This study focuses on training and validating a deep learning model using MRI images to detect and locate brain tumors. The human brain, a vital organ located within the skull, is the central component of the nervous system. It controls all bodily functions and enables humans to interact with their environment, think, and express emotions. Understanding the brain's structure is essential for grasping how tumors affect its functionality. Brain tumors are generally classified into two types: primary and secondary. Primary brain tumors, such as benign tumors, grow slowly and originate from non-neuronal brain cells, like astrocytes, forming tumors such as gliomas.

Although less aggressive, primary tumors exert pressure on the brain, which can disrupt its functionality. Secondary brain tumors, on the other hand, are more aggressive and metastatic. These malignant tumors originate in other parts of the body, such as the lungs, kidneys, or bladder, and spread to the brain. Secondary tumors grow rapidly, making them more dangerous and challenging to treat. They often result from advanced cancers elsewhere in the body, with cancerous cells traveling to the brain and other tissues. This study leverages MRI imaging and deep learning to address the challenges of brain tumor detection, aiming for improved accuracy in identifying and classifying these life-threatening conditions. Medical imaging techniques play a vital role in diagnosing internal conditions within the human body. Among the numerous challenges in image processing, medical image classification stands out as both demanding and highly rewarding. One of the most common challenges in this field is identifying tumors or detecting cancer through image analysis. In recent years, medical professionals have increasingly adopted advanced technologies to detect tumors in a minimally invasive manner. Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) have emerged as effective tools for identifying abnormalities across different regions of the body. The growing need for rapid and unbiased analysis of large medical datasets has fueled significant interest in MRI-based image processing for brain tumor detection. This process requires sophisticated computational tools for quantification and visualization due to the diversity of image formats. Automated brain tumor diagnosis from MRI scans has become critically important, as it eliminates the need for manual data analysis and enhances the efficiency and accuracy of medical assessments [1].

This paper introduces a CNN-based architecture designed for pre-diagnosis tumor detection while ensuring patient privacy in smart healthcare systems. The proposed framework begins by cropping MR images to the skull region, followed by the application of denoising filters and histogram equalization to enhance image quality. A data augmentation strategy is employed to ensure stable learning and improve model generalization. Subsequently, three distinct CNN models are implemented, each paired with a different optimizer, to analyze and evaluate their performance in brain tumor detection and pre-diagnosis while maintaining patient privacy.

Fig. 1.Brain MRI Scan Images

The above figure 1 displays multiple brain MRI scan slices, which are typically used for diagnosing brain-related abnormalities such as tumors, lesions, or other structural irregularities. Each slice represents a cross-sectional view of the brain, allowing medical professionals to analyze different layers and regions. By examining these images, abnormalities like unusual growths, differences in tissue density, or disrupted structures can be identified. In this figure 1, a specific slice is being highlighted using a pointer, indicating an area of interest that may require closer examination. MRI scans are widely preferred over CT scans due to their superior ability to differentiate between soft tissues, providing detailed information essential for detecting and analyzing brain tumors or other anomalies.

## II. LITERATURE SURVEY

Deep learning-based image processing healthcare systems represent a state-of-the-art approach to medical imaging and diagnostics, utilizing advanced artificial intelligence (AI) techniques to analyze and interpret medical images with exceptional accuracy and efficiency. These systems have shown outstanding performance in various medical imaging tasks, including disease diagnosis, lesion detection, tumor segmentation, and treatment planning. In the context of brain tumor detection, numerous survey studies [2] have explored a range of deep learning architectures and methodologies applied to this domain. These studies evaluate the techniques based on metrics such as sensitivity, specificity, accuracy, and computational efficiency, highlighting their unique strengths and limitations across diverse clinical applications. CNN-based methods, in particular, have demonstrated significant advancements in analyzing different types of tumors, especially when applied to large datasets [3], [4], [5].

Rana et al. [6] conducted an extensive literature review focusing on the detection and classification of various diseases using deep learning algorithms. Their study provides valuable insights into a wide range of machine learning (ML) and deep learning (DL) approaches, imaging modalities, evaluation metrics, and datasets utilized in disease detection and classification. The review explores fundamental convolutional neural network (CNN) architectures, datasets, and advanced DL techniques for tissue segmentation integrated with classification tasks [7]. Additionally, the authors highlight ongoing research in CNNs and Autoencoders, offering a roadmap for researchers to identify potential areas for future exploration. The study concludes with an analysis of possible advancements and the unresolved challenges in brain tumor segmentation. Allah et al. [8] propose the Edge U-Net model, a deep convolutional neural network (DCNN) based on an encoder-decoder structure inspired by the U-Net architecture. This model aims to enhance performance in tasks requiring precise segmentation and classification.

Anagun et al. [9] designed a brain tumor diagnosis system leveraging Convolutional Neural Networks (CNNs) built on the EfficientNetv2 architecture. This model was further optimized using the Ranger optimizer and advanced pre-processing techniques to enhance performance. The proposed system was benchmarked against prominent deep learning architectures, including ResNet18, ResNet200d, and InceptionV4, demonstrating its capability to effectively identify brain tumors by analyzing their spatial features.

The absence of robust encryption protocols and secure data transmission methods in many AI-assisted systems amplifies the risks associated with data breaches and unauthorized access. Research by Zlatolas et al. [10] highlights the insufficiency of current security measures in effectively addressing these vulnerabilities. This gap underscores a critical disconnect between the advancement of sophisticated AI models and the integration of privacy-by-design principles, leaving systems inadequately equipped to ensure data security and user privacy.

Hamza et al. [11] explored the use of homomorphic encryption, showcasing its potential as a privacy-preserving technique. However, their study also emphasized the performance trade-offs, such as increased computational overhead, which hinder its applicability in real-time scenarios. This highlights the urgent need for research focused on developing encryption methods tailored for deep learning applications in healthcare. Such methods must strike a balance between robust security and the operational requirements of speed and efficiency to ensure practicality in real-world implementations.

Habib et al. [12] employed an Artificial Neural Network (ANN) to detect brain tumors using a dataset similar to the one in this study. Their neural network featured a sequential design with two max-pooling layers and a 2D convolutional (Conv2D) layer, achieving enhanced accuracy in tumor detection. In a related effort, Lin and Chang utilized K-means clustering combined with color-based segmentation to identify brain tumor regions. Their approach converted grayscale images into color-space clusters, effectively grouping similar regions for improved tracking. Both studies relied on MRI scans due to the intricate variations in tumor sizes and shapes, underscoring the challenges associated with accurate tumor classification.

Other approaches explored for brain tumor detection include supervised learning techniques such as Decision Trees and Multi-Layer Perceptrons. While these methods have shown potential, studies highlight that image processing and machine learning techniques are not entirely error-proof, as misdiagnoses remain a concern. To mitigate variability and enhance model robustness, some researchers have incorporated MRI augmentation, modifying images in terms of angles and perspectives to diversify the training dataset. This strategy has delivered promising results, particularly when integrated with architectures like Convolutional Neural Networks (CNNs) and LinkNet.

Ayesha Jabbar et al. [13] proposed a hybrid deep learning model for automatic brain tumor classification, combining CapsNet (Capsule Neural Network) and VGGNet to address the challenge of large data requirements often associated with deep learning in tumor classification. The model was evaluated using the Brats-2020 and Brats-2019 datasets, achieving impressive results with 99% accuracy, 98% sensitivity, and 99% specificity, as confirmed by experimental data. However, this approach faces challenges, particularly its high complexity and limited generalizability.

Muhammad Imran Sharif et al. [14] developed an automated deep learning method for classifying brain cancers into multiple categories. Their approach utilized a refined Densenet201 pre-trained deep learning framework for feature engineering, alongside a modified evolutionary algorithm and entropy-Kurtosis-based high feature values for feature selection. A Support Vector Machine (SVM) cubic classifier was then applied for tumor classification. The methodology was evaluated on the BRATS2018 and BRATS2019 datasets, achieving an average accuracy of 95%. However, the approach suffers from longer training times, which limits its practical applicability in real-world scenarios.

Havaei et al. [15] in their paper "Brain Tumor Segmentation with Deep Neural Networks," focused on automating brain tumor segmentation using deep neural networks (DNNs). Their CNN-based model was trained on labeled MRI datasets, achieving superior accuracy compared to traditional segmentation techniques.

Islam et al. [16] introduced a hybrid approach that combines CNNs and SVMs for brain tumor detection, improving both accuracy and efficiency over traditional methods. Similarly, Zikic et al. [17] demonstrated the robustness of CNNs for tumor segmentation, suggesting their potential to enhance clinical decision-making processes.

Wang et al. proposed a user-interactive deep learning application featuring multiple CNN architectures for MRI image segmentation. This approach allowed users to highlight specific brain regions, offering flexibility in clinical applications. Their study also explored GoogleNet (Inception-v1), a faster and more resource-efficient architecture, featuring components like rectified linear activation functions and average pooling layers.

AlexNet, another architecture discussed, is deeper and more advanced, comprising five convolutional layers (mostly paired with max pooling) and three fully connected layers. It uses a 1000-class SoftMax for output and operates on dual GPUs to reduce error rates. AlexNet has been enhanced by Zeit architecture, which visualizes feature development during training and maps intermediate-layer activity back to the original image space for improved debugging and performance.

***HARDWARE REQUIREMENTS***

Hard Disk: 500GB and Above

RAM: 4GB and Above

Processor: I3 and Above.

***SOFTWARE REQUIREMENTS***

*A.* Visual Studio Code (VSS): is a free, open-source source-code editor developed by Microsoft. It's available for Windows, macOS, and Linux operating systems. Here's some information about VS Code.

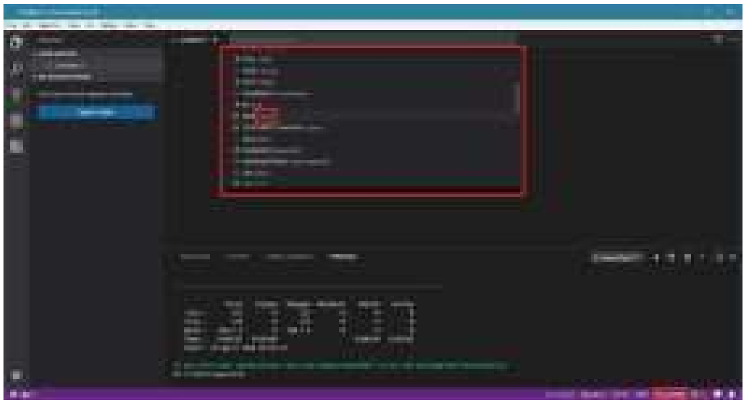

Fig. 2. Visual Studio Code (VSS)

*B.* Jupyter Notebook

Jupyter Notebook is an open-source web application that allows you to create and share documents that contain live code, equations, visualizations, and narrative text. It supports various programming languages, but it is most commonly used with Python.

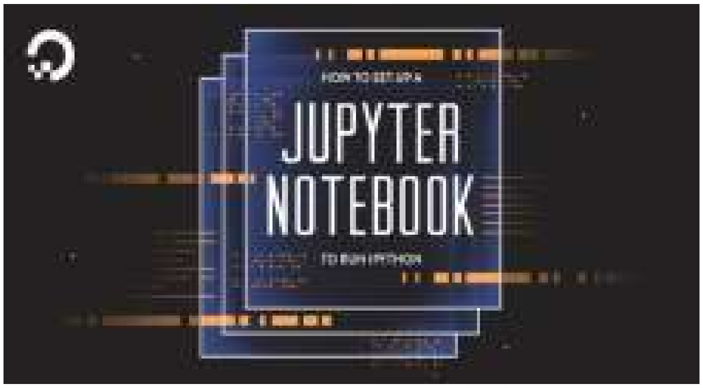


Fig. 3. Jupyter Notebook

## III. ALGORITHMS USED

Conventional Neural Networks: Convolutional Neural Networks (CNNs) are a specialized deep learning architecture designed for tasks involving image recognition and processing. These networks consist of several layers, including convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. Modeled after the human visual system, CNNs excel at identifying hierarchical patterns and spatial relationships in image data, making them particularly effective for analyzing complex visual inputs.

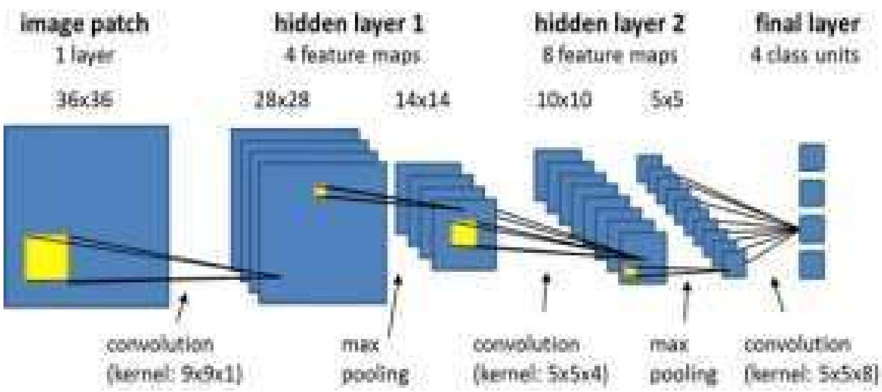


Fig. 4. CNN Algorithm


Fig. 5. FLASK Interface Glioma Tumor

CNNs are trained on extensive datasets of labeled images, enabling the network to identify patterns and features linked to specific objects or classes. They have consistently delivered state-of-the-art results in numerous computer vision tasks. Their strength lies in their ability to automatically learn hierarchical feature representations, making them ideal for applications where understanding spatial relationships and patterns is critical for accurate predictions. Support Vector Machine (SVM) is a supervised machine learning algorithm used for both classification and regression. Though we say regression problems as well it's best suited for classification. The main objective of the SVM algorithm is to find the optimal hyperplane in an N-dimensional space that can separate the data points in different classes in the feature space. The hyperplane tries that the margin betweenthe closest points of different classes should be as maximumas possible. The dimension of the hyperplane depends uponthe number of features. If the number of input features is two, then the hyperplane is just a line. If the number of input features is three, then the hyperplane becomes a 2-D plane.It becomes difficult to imagine when the number of features exceeds three. Let's consider two independent variables x1,x2, and one dependent variable which is either a blue circleor a red circle.

## IV. METHODOLOGY

Image Acquisition: The Primary Phase is acquiring images. After the Images collection, the obtained images have to be prepared with a wide range of vision. First capture the input images fromavailable source.

Pre-Processing: The images which are collected are subjected to pre- pro- cessing. In Pre-processing stage basic steps are image resizingand applying Gaussian filters for a perfect input clear image for easy identification of an image. Pre-processed images will be segmented digitally into various pixels. We do this segmentation for an image is to modify its representation to have more clarity to analyze the images. Image Segmentation: In the first stage, the pre-processed brain Magnetic Reso- nance image will be transformed into a binary image with a threshold of 128 for the cutoff. Pixel values higher than the specified thresholds are mapped as white, with other regions marked as black; these two allow various regions to be gener- ated around the disease. In the second stage, an erosion processof morphology is used to extract white pixels. Eventually, the eroded area and the original image are separated into twoequal areas, and the region with black pixels from the eroding is counted as a mask of brain Magnetic Resonance image. In this paper, wavelet transformation is used for the efficient segmentation of the brain Magnetic Resonance image. Figure 3 shows the fully automatic heterogeneous segmentation. Figure 3(a) shows the axial image and its segmentation figure 3(b) Coronal image and its segmentation figure 3 (c) Sagittal images and its segmentation.

Feature Extraction: In the feature extraction process, we can implement the effective texture operator which labels the pixels of an image. Here we extract the features and characteristics of Images for easy detection of brain tumor.

Classification: Convolutional neural networks algorithm is used for classification of brain images. It is producing the best results for the images. Tumor Detection: Finally, analyze the image using filters and Convolutional neural networks algorithm to detect the tumor or non-tumor.

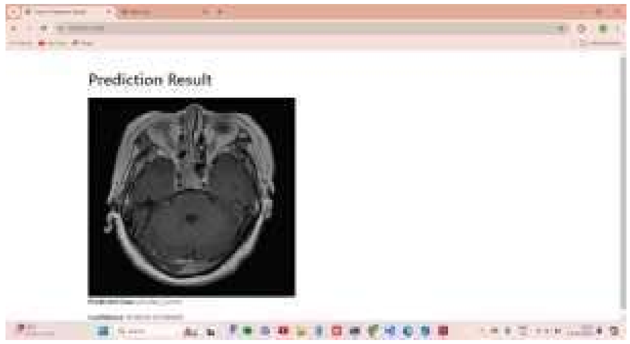


Fig. 6. FLASK Interface Glioma Tumor

## V. RESULTS

Dataset of almost 3000 images of different types of tumors are collected from kaggle. The output interface is created in FLASK, a python Web Framework. The output is shown below the metrics demonstrate that the model achieves an excellent balance between sensitivity and specificity, indicating that it reliably detects abnormal brain images without misclassifying normal images. Additionally, the high precision ensures that the abnormal predictions are trustworthy, and the overall high accuracy reflects the model's robust performance on the dataset.

Table1: Performance of the proposed method

| Performance | |
|---|---|
| Accuracy | 98.25 |
| Sensitivity | 98.56 |
| Specificity | 98.57 |
| Precision | 98.38 |

***Performance Metrics***: The system's performance is evaluated based on the following metrics:

- ***Accuracy: 98.25%***
  Accuracy represents the overall correctness of the model in predicting brain tumors. It indicates the proportion of correct predictions (both positive and negative) out of the total predictions made.
- ***Sensitivity: 98.56%***
  Sensitivity (or recall) measures the model's ability to correctly identify positive cases (e.g., detecting actual tumors). A high sensitivity ensures that very few true tumor cases are missed.
- ***Specificity: 98.57%***
  Specificity measures the model's ability to correctly identify negative cases (e.g., absence of tumors). This ensures that the model effectively avoids false positives.
- ***Precision: 98.38%***
  Precision represents the accuracy of positive predictions, reflecting the proportion of correctly predicted tumor cases among all predicted positives.

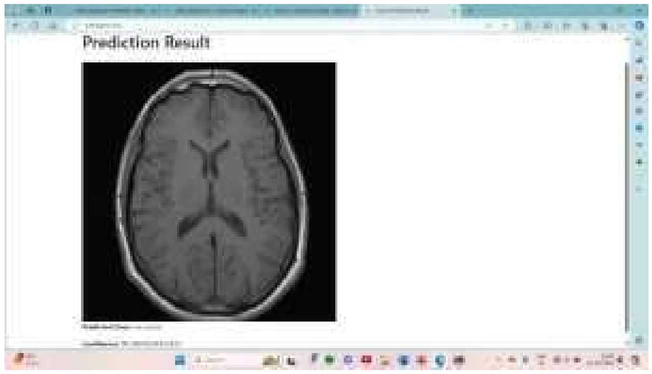


Fig.7. FLASK Interface showing Pituitary Tumor

The above figure 7 displays the user interface of a Flask-based web application, which provides predictions for brain tumor detection. The showcased MRI scan corresponds to a prediction result indicating the presence of a pituitary tumor. The interface allows users to upload brain MRI images for analysis, leveraging a trained deep learning model for automatic classification and diagnosis. The prediction result is displayed along with the uploaded image, enabling users such as clinicians or patients to visually confirm the affected region. This web-based system enhances accessibility and user-friendliness by providing immediate tumor detection outcomes, serving as a valuable tool for smart healthcare applications.

Fig. 8. Accuracy

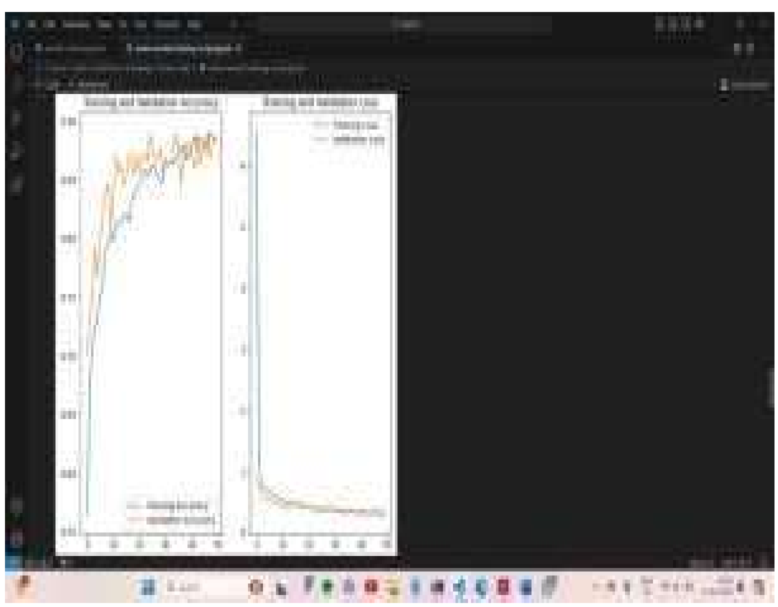

Fig. 9. Training and Validation Accuracy

Fig. 10. Confusion Matrix

## VI. CONCLUSION

This study aims to establish a streamlined yet effective approach to brain image classification, ensuring high accuracy and efficiency. The method builds on traditional techniques, integrating CNN-based segmentation for identifying key regions of interest, and SVM for extracting texture and shape features. ELM is further applied for the final classification task, categorizing the images into normal or abnormal brain images. SVM employs a series of feed-forward layers to perform these tasks efficiently. The study leverages the BRATS 2020 Image Database, a widely recognized dataset for brain tumor research. During the implementation phase, pre-trained models are utilized, with only the top layer retrained for fine-tuning. This approach significantly simplifies the model structure while maintaining high performance metrics. The model achieves exceptional results, with an accuracy of 98.25%, sensitivity of 98.56%, specificity of 98.57%, and precision of 98.38%, showcasing its reliability for brain image classification tasks.

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