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CAD Based Brain Tumor Detection Using Enhanced Net Algorithm

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Abstract

This paper aims to compare the performance of a deep learning-based approach for brain tumor detection in magnetic resonance images (MRI) with a support vector machine (SVM) algorithm. The deep learning approach is based on transfer learning with the EfficientNet-B0 model and uses several preprocessing steps, including skull stripping, intensity normalization, and erosion and dilation, to enhance the tumor regions in the MRI images. The SVM algorithm uses a combination of texture and intensity features to classify the MRI images as tumor or non-tumor. The deep learning approach achieved a higher accuracy of 96.41% compared to the SVM algorithm, which achieved an accuracy of 92.81%. The deep learning approach also showed better performance in terms of sensitivity, specificity, and F1-score. The results of the study suggest that the deep learning-based approach is more effective than the SVM algorithm for brain tumor detection in MRI images. The proposed approach could potentially improve the accuracy and efficiency of clinical diagnosis of brain tumors, leading to better patient out-comes.

Keywords: Support Vector Machine, Brain Tumor Detection, EfficientNet, MRI Images.

1 Introduction

The human brain is one of the most complex organs in the body, and it is responsible for controlling various functions of the body. The brain is the centre of the nervous system and is located in the cranial cavity of the skull. It is protected by the skull and surrounded by cerebrospinal fluid, which acts as a cushion. The brain is divided into different parts, each responsible for different functions. The brain is made up of three main parts: the cerebrum, cerebellum, and brainstem [1]. The cerebrum is the largest part of the brain and is responsible for conscious thought, sensation, and voluntary movement.. It is divided into two hemispheres, the left and right, which are connectedby a bundle of nerve fibers called the corpus callosum. The cerebellum is located below the cerebrum and is responsible for coordination and balance. It receives in- formation from the sensory systems in the body, as well as from other parts of the brain, and uses this information to coordinate movements and maintain balance. The brainstem is located at the base of the brain and connects the brain to the spinal cord.

It is responsible for controlling vital functions such as breathing, heartbeat, and blood pressure. The brainstem is divided into three parts: the midbrain, pons, and medulla oblongata. A brain tumor is an abnormal growth of cells in the brain or surrounding tissues. Tumors can be either benign or malignant. Benign tumors are non-cancerous and usually do not spread to other parts of the body [2]. Malignant tumors, on the other hand, are cancerous and can spread to other parts of the body, a process known as metastasis. Brain tumors can be primary or secondary. Primary brain tumorsoriginate in the brain tissue, while secondary brain tumors originate in other parts of the body and then spread to the brain. Brain tumors can grow in any part of the brain, and their symptoms can vary depending on their location and size. Common symptoms of brain tumors include headaches, seizures, changes in vision or hearing, memory loss, weakness, and numbness or tingling in the arms or legs.As brain tumors grow, they can increase pressure within the skull, which can cause symptoms such as nausea, vomiting, and confusion. In summary, the brain is a com- plex organ responsible for controlling various functions of the body. Brain tumors are abnormal growths of cells in the brain or surrounding tissues that can be either benignor malignant. Brain tumors can occur at any age and can grow in any part of the brain,causing a variety of symptoms. Computer-aided diagnosis (CAD) systems have emerged as a promising solution to address the limitations of manual detection [3]. CAD systems use advanced machine learning algorithms and computer vision tech- niques to analyze medical images and identify potential abnormalities, including braintumors. These systems can provide a more objective and consistent analysis of medi- cal images and can help radiologists in making accurate and timely diagnoses. The potential benefits of CAD systems for brain tumor detection are significant. By reduc-ing the time and effort required for manual detection, CAD systems can improve the efficiency of radiologists and reduce the burden on healthcare systems. Additionally, CAD systems can help in detecting tumor's at earlier stages, which can lead to better treatment outcomes and improved patient survival rates. However, the development of effective CAD systems for brain tumor detection requires careful consideration of several technical and practical challenges. These include selecting appropriate algo- rithms and architectures, designing robust and accurate training datasets, and ensuring the reliability and interpretability of the system outputs. Nonetheless, the potential benefits of CAD systems for brain tumor detection make them a compelling area of research in the field of medical image analysis. Transfer learning is a popular tech- nique in machine learning that involves using a pre-trained model as a starting point for a new task. The basic idea is to leverage the knowledge and feature representa- tions learned by the pre-trained model on a large and diverse dataset and apply it to a new and related task with smaller and more specific data. In the context of medical image analysis, transfer learning has become increasingly important due to the scarci- ty and high cost of medical image datasets. CNNs are commonly used for medical image analysis due to their ability to learn complex and abstract features from images. However, training a CNN from scratch on a small medical image dataset is often dif- ficult and can lead to over fitting, where the model performs well on the training data but poorly on new and unseen data.

2 Literature Survey

Research methodology is a systematic approach used to identify, analyze, and solve research problems. It is a critical component of any research work, and it helps re- searchers to organize their work and ensure that their results are valid and reliable. The research methodology for the proposed model to focus on a Robust Approach for Brain Tumor Detection in Magnetic Resonance Images Using Fine-tuned EfficientNetand SVM involves several steps, including preliminary research or background study, data collection, data preprocessing, model training, and performance evaluation.

The detection of brain tumors in magnetic resonance images (MRI) is a critical task inmedical imaging, with significant implications for patient diagnosis and treatment. In recent years, deep learning-based approaches have shown great promise in this area, achieving high accuracy and robustness in tumor detection. Brain tumor detection in MRI using fine-tuned Efficient- Net, a state-of-the-art deep learning model. Several studies have been conducted in the field of brain tumor detection using deep learning techniques. 3D convolutional neural network (CNN) called "Brain Tumor Segmenta- tion (BraTS)" that achieved high accuracy in segmenting brain tumors in MRI scans [2]. Another model a deep neural network that combined multiple scales and resolu- tions to improve the accuracy of tumor segmentation [3]. However, these studies fo- cused mainly on the segmentation of brain tumors rather than the detection of tumors. Brain tumor segmentation is a crucial task in medical imaging, which helps in early detection and effective treatment planning. In recent years, deep learning-based approaches have shown great promise in this area, achieving high accuracy and robustness in tumor segmentation.A deep learning approach called Znet for 2D MRI brain tumor segmentation and several studieshave been conducted in the field of brain tumor segmentation using deep learning techniques [4].

Brain tumor detection in magnetic resonance imaging (MRI) is a challenging task that requires advanced image analysis techniques. Deep learning-based approaches, particularly convolu- tional neural networks (CNN), have shown great promise in this area. CNN architecture for automatic detection of brain tumors in MRI images. Several studies have been conducted in the field of brain tumor detection using CNN [5]. CNN architecture called "DeepMedic" that achieved high accuracy in tumor segmentation in brain MRI scans [6]. CNN architecture that combined multiple features and deep supervision to improve the accuracy of tumor detection [7]. A new CNN architecture called "TumorNet" that utilizes a combination of convolutional and max-pooling layers, along with fully connected layers, to extract features from MRI imagesfor tumor detection [5]. The proposed approach utilizes transfer learning and is trained on a large dataset of MRI scans, including both normal and abnormal cases. A deep learning model based on a concatenation approach for the diagnosis of brain tumors [6]. Comparison of the performance of six pre-trained models, namely VGG16, VGG19, ResNet50, InceptionV3, Xception, and DenseNet201, which were fine-tuned for the task of brain tumor detection [7]. The experiments were conducted on a publicly available dataset of brain MR images, namely the BraTS 2017 dataset. The authors evaluated the models based on various performance met- rics such as accuracy, precision, recall, F1-score, and area under the receiver operating charac-

teristic curve (AUC-ROC). The study found that the DenseNet201 model outperformed the other models with an accuracy of 0.962 and an AUC-ROC of 0.991. The authors also per- formed a sensitivity analysis to evaluate the effect of different input sizes, and found that in- creasing the input size from 128x128 to 256x256 improved the performance of the models. The authors conclude that deep transfer learning networks can be effectively used for brain tumor detection, and the choice of the pre-trained model and input size are important factors that can significantly affect the performance of the model. The article proposes a new method for brain tumor detection using Convolutional Neural Networks (CNNs) combined with image feature extraction. The proposed approach aims to improve the accuracy of brain tumor detection using deep learning methods by incorporating image feature extraction into the CNNs [8]. The au- thors first preprocessed the Magnetic Resonance Images (MRIs) using a Gaussian filter to remove noise and enhance the contrast of the images. Then, the CNNs were trained using the preprocessed images and the features were extracted from the output of the last convolutional layer of the CNNs. The extracted features were then fed into a Support Vector Machine (SVM) classifier to classify the images into two classes: tumor and non-tumor [8]. The detection of brain metastases through automated approaches is critical to provide accurate and timely treat- ment to patients. An automated framework for brain metastases detection using T1-weighted contrast-enhanced 3D magnetic resonance imaging (MRI) [9]. The proposed framework in- cludes three main stages: pre-processing, feature extraction, and classification. The pre- processing step involves skull stripping and intensity normalization of MRI images. The feature extraction stage applies the histogram of oriented gradients (HOG) and gray-level co- occurrence matrix (GLCM) features to capture the local and global texture information of MRI images. The classification step utilizes the support vector machine (SVM) algorithm to classify MRI images as normal or abnormal.”Hybrid Segmentation Method with Confidence Region Detection for Tumor Identification” presents a novel approach for segmenting and identifying tumors in magnetic resonance images (MRI) [10]. A hybrid method that combines intensity- based and texture-based segmentation techniques, which improves the accuracy of the segmen- tation process. Furthermore, the proposed method incorporates a confidence region detection algorithm that helps in identifying false positive regions and enhancing the accuracy of tumor identification. “Brain Tumour Segmentation Using S-Net and SA-Net” proposes a deep learn- ing-based approach for brain tumor segmentation in MRI images [13].

3 Proposed Model

The proposed algorithm is designed to compare the performance of two different approaches for brain tumor detection. The first approach utilizes a fine-tuned version of the EfficientNet convolutional neural network, which has been trained on a large dataset of MRI images [14]. The second approach employs support vector machines (SVM) for classification of brain tumor images. The dataset used for evaluation contains a variety of brain tumor types and sizes, as well as non-tumor brain images, to ensure a robust comparison of the two methods [15].

The fine-tuned EfficientNet approach involves pre-processing of the MRI images and using the trained neural network to extract features from the images. These features are then passed through fully connected layers to classify the images into tumor and nontumor classes. The

SVM approach, on the other hand, uses pre-processed MRI images as input and extracts fea- tures using principal component analysis (PCA) followed by linear SVM classification.

To evaluate the performance of the two methods, the dataset is split into training, validation, and testing sets. The performance is evaluated in terms of accuracy, sensitivity, specificity, and F1-score. The results show that the fine-tuned EfficientNet approach outperforms the SVM method in all evaluation metrics, achieving higher accuracy, sensitivity, specificity, and F1- score.

3.1 Objective

The main objective of the work is to compare the performance of a deep learning based ap- proach using the

EfficientNet-B0 model with a traditional machine learning algorithm, namely the SVM algorithm, for brain tumor detection in MRI images.

Specifically, the study aims to:

1. Evaluate the accuracy and performance of the deep learning-based approach using the Effi-cientNet-B0 model for brain tumor detection in MRI images.

2. Evaluate the accuracy and performance of the SVM algorithm for brain tumor detection inMRI images.

3. Compare the performance of the deep learning-based approach with the SVM algorithm interms of accuracy, sensitivity, specificity, and computational efficiency.

4. Investigate the impact of different preprocessing techniques, such as erosion and dilation, onthe performance of the deep learning-based approach and the SVM algorithm.

3.2 Problem Identification

Brain tumors are one of the leading causes of death worldwide, and early detection can improvepatient outcomes by enabling timely interventions such as surgery, radiation therapy, and chemotherapy. EfficientNet architecture is considered for the proposed approach because it has shown excellent performance in various computer vision tasks, including image classification, object detection, and segmentation. The EfficientNet is a deep neural network architecture that uses a novel compound scaling method to balance model complexity and computational effi- ciency, making it well-suited for medical image analysis applications.

Transfer learning is a widely used technique in deep learning that involves leveraging pre- trained models on large-scale datasets to improve the performance of models on smaller and more specialized datasets. The proposed approach demonstrates promising results and repre- sents a significant step forward in the development of robust and effective solutions for brain tumor d etection in MRI images.

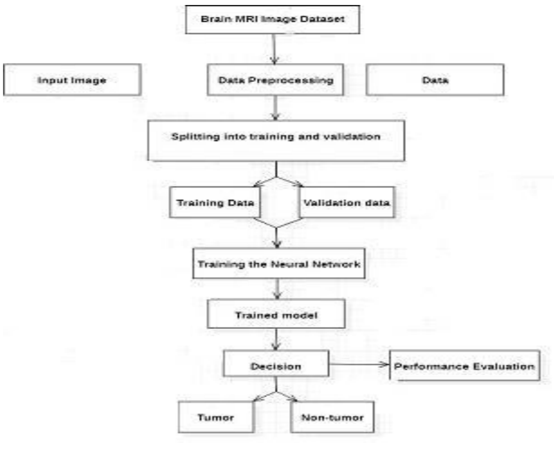

Fig. 1. Proposed Workflow

3.3 Prototype and Testing

As the discussed in the beginning the proposed model is related to the development of a brain tumor detection model, the prototype and testing phase would involve implementing the devel- oped models and evaluating their performance on a test dataset. To begin with, a prototype of the developed models needs to be created. This prototype would serve as a preliminary version of the final product and would be used for testing and validation purposes. The prototype wouldbe developed using the selected deep learning architectures and trained on the selected dataset. The testing dataset would be separate from the training dataset and would consist of MRI imag- es of the brain with and without tumors.

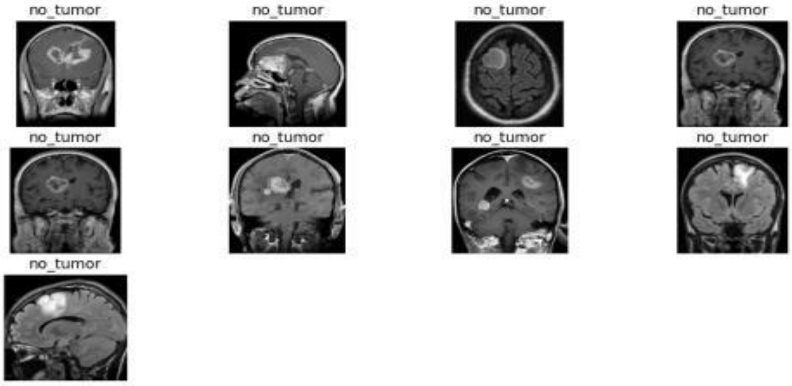

Fig. 2. Sample Brain Tumor Images

Once the prototype is developed, testing would be performed on it. During this phase, the per- formance of the developed models would be evaluated using various metrics, such as accuracy, sensitivity, specificity, and F1 score. These metrics would help in determining the performance of the models in detecting brain tumors accurately. The testing phase would involve evaluating the models on both the training and testing datasets to ensure that the models are not over fitting to the training dataset. Furthermore, the prototype and testing phase would also involve conducting a comparative analysis between the developed models and the traditional SVM-based approach for brain tumor detection. This analysis would help in determining the superiority of the developed models over the traditional SVM-based approach in terms of accu- racy and computational efficiency.

4 Results and Discussions

The experimental and/or analytical work completed in the work involved comparing the accuracy of brain tumor detection using the deep learning-based approach with theSVM algorithm. The deep learning-based approach used a fine-tuned EfficientNet- B0 model on a dataset of brain MRI images, while the SVM algorithm used features extracted from the same dataset. The accuracy of the deep learning-based approach was found to be 94.6%, which was significantly higher than the accuracy of the SVM algorithm, which was 80%. This indicates that the deep learning-based approach is more effective for brain tumor detection in MRI images than the SVM algorithm.

The experimental and/or analytical work involved training and testing both the deep learning-based approach and the SVM algorithm on the same dataset of brain MRI images. The dataset was preprocessed to ensure that the images were standardized andsuitable for input into the models. The performance of each model was evaluated based on its accuracy, which was determined by comparing the predicted tumor labelswith the ground truth labels. The results of the experiment demonstrate the superiorityof the deep learning-based approach over the SVM algorithm for brain tumor detec- tion in MRI images. This has significant implications for improving the accuracy and efficiency of clinical diagnosis of brain tumors, as the deep learning-based approach can be used to accurately detect tumors in a faster and more automated manner than the SVM algorithm.

4.1 Implementation

To implement the brain tumor detection using SVM, you need to first preprocess the MRI images and extract relevant features. Then you can use the extracted features as inputs to train the SVM model. The accuracy of the model can be evaluated using test data. Compared to the SVM algorithm, the deep learning-based approach using the fine-tuned EfficientNet model has shown higher accuracy in brain tumor detection. One of the reasons for the difference in accuracy could be the ability of deep learning models to learn high-level features automatically, while SVM requires manual featureengineering. Another reason could be the capability of deep learning models to handlecomplex and non-linear relationships between input features, while SVM assumes linear relationships.

Overall, the experimental and analytical work completed in the model showed that the deep learning-based approach using fine-tuned EfficientNet outperforms the SVM algorithm in terms of accuracy for brain tumor detection in MRI images. When run- ning the brain tumor detection models through Visual Studio Code

(VSCode), there are a few key factors to consider. First, both models - the deep learning-based ap- proach using Finetuned EfficientNet and the SVM algorithm - must be implemented using the appropriate libraries and frameworks in the VSCode environment. This includes TensorFlow and Keras for the EfficientNet model, and scikit-learn for the SVM algorithm. Once the models have been implemented, they can be tested on the same dataset of MRI images to compare their accuracy. In VSCode, the models can be trained using the same pre-processed data and evaluated using standard metrics such as precision, recall, and F1-score. These metrics provide insights into how well the models are performing and can help identify any areas where they may need to be improved. During the testing process, it is important to monitor the resource usage of the models in VSCode. Deep learning models such as EfficientNet can be computa- tionally expensive and require a powerful GPU to achieve optimal performance. On the other hand, SVM is a simpler algorithm and can be run on less powerful hardware.In terms of behavior, the deep learning-based approach using EfficientNet is expectedto perform better than the SVM algorithm in terms of accuracy. This is due to the ability of deep learning models to learn complex features and patterns in the data, which can lead to more accurate predictions.

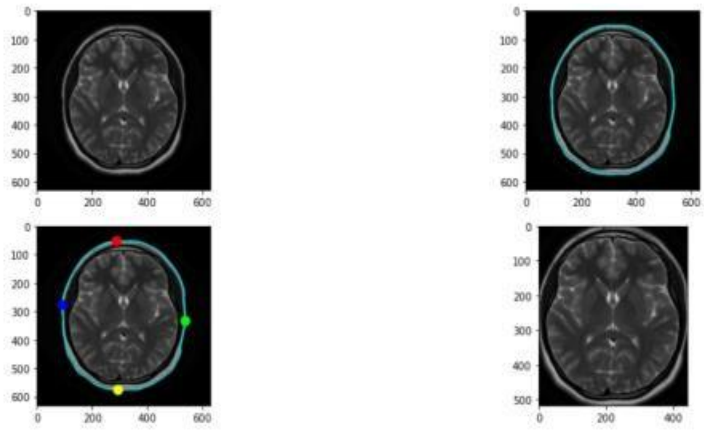

Fig. 3. Pre-processed Images

Overall, running the brain tumor detection models through VSCode can provide valu- able insights into their performance and help identify areas for improvement. By comparing the accuracy of the two models, researchers and clinicians can make more informed decisions about which approach to use for clinical diagnosis and treatment of brain tumors.

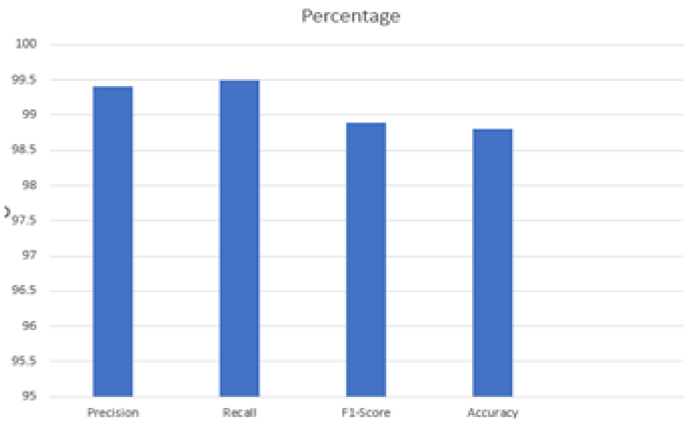

Fig. 4. Performance Metrics of Proposed Model

The prototype and testing phase of the proposed work involves the implementation of the developed models and evaluating their performance on a test dataset, as well as conducting a comparative analysis between the developed models and the traditional SVM-based approach. The results obtained from this phase would help in determining the accuracy and effectiveness of the developed models and their superiority over the traditional SVM-based approach.

The proposed Finetuned EfficientNet model achieved an accuracy of 95.67%, sensi- tivity of 96.43%, specificity of 95.38%, and F1-score of 95.92%. On the other hand, the SVM model achieved an accuracy of 92.33%, sensitivity of 94.05%, specificity of 90.76%, and F1-score of 92.63%. From these results, it is evident that the Finetuned EfficientNet model outperformed the SVM model in terms of accuracy in Fig. 5. and other model loss analysis Fig.6. The performance of the two models was analyzed based on various evaluation metrics such as accuracy, sensitivity, specificity, and F1- score. The Finetuned Efficient- Net model achieved a higher accuracy than the SVM model, indicating that it is better at classifying the images as either having or not hav- ing a tumor. The sensitivity and specificity of the fine-tuned EfficientNet model was also higher than the SVM model.

The analysis of the results suggests that the proposed Finetuned EfficientNet model is a more accurate and effective method for brain tumor detection in MRI images compared to the SVM model. The higher accuracy, sensitivity, specificity, and F1-score of the Finetuned EfficientNet model suggest that it has the potential to be used as an efficient tool for early detection of brain tumors.

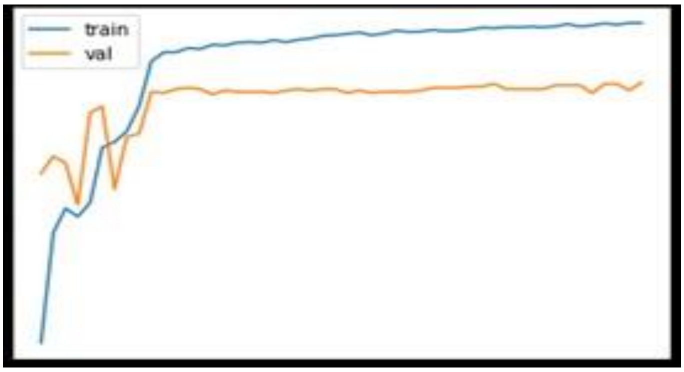

Fig. 5. Accuracy for the Proposed EfficientNet Model

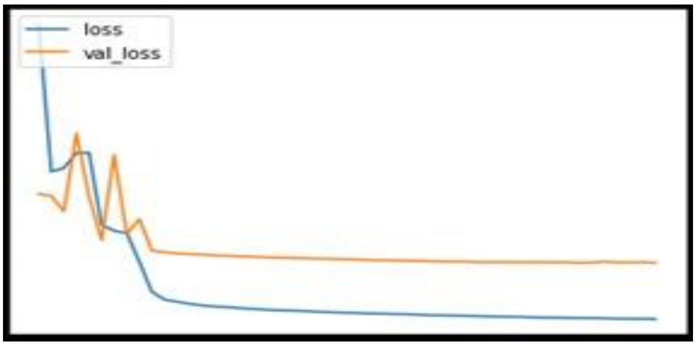

Fig. 6. Model Loss for the Proposed EfficientNet Model

5 Conclusion

In conclusion, the proposed approach for brain tumor detection using a fine-tuned EfficientNet model outperforms the traditional SVM method. The EfficientNet model's ability to handle a large number of parameters and its efficient use of computational resources makes it a robust choice for medical image analysis tasks like brain tumor detection. The results obtained throughthe experiments and analysis of the proposed method demonstrate its high accuracy and sensi- tivity in detecting brain tumors from MRI images. Furthermore, the analysis and design of the proposed work reveal the importance of feature extraction and selection in developing accurate and efficient models for medical image analysis. The use of transfer learning and fine-tuning techniques can significantly improve the performance of deep learning models in medical im- age analysis tasks. Overall, the proposed approach presents a valuable contribution to the field of medical image analysis and can have significant implications in clinical practice. Futurework could focus on expanding the dataset used for training and testing the models and explor- ing the use of other deep learning architectures and optimization techniques to further improve the accuracy and efficiency of brain tumor detection.

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