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Brain Tumor Detection Using Deep Convolutional Neural Network

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Abstract: This study presents a deep learning method for classifying brain tumors from magnetic resonance imaging (MRI) data is presented. We used a publically accessible dataset that included pictures of meningiomas, gliomas, pituitary tumors, and healthy brains to train a model using the ResNet-18 architecture. To improve model resilience, data augmentation methods such as rotation, color jitter, affine transformations, random horizontal flipping, and scaling were used. The model's ability to differentiate between various forms of brain tumors was demonstrated by its 98.74% training accuracy and 98.70% validation accuracy across 20 epochs. These findings imply that the suggested approach may be a useful instrument for helping medical professionals diagnose brain tumors accurately and quickly.

Keywords: Braintumor, ResNet-18, Imagenet, Convolution Neural Network, Cross entropy Loss, StepLR

Research Paper

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I. INTRODUCTION

Brain tumor are serious and life-threatening conditions that require accurate and timely diagnosis to ensure effective treatment. Magnetic Resonance Imaging (MRI)[1] is a critical tool in this process, supplying precise brain pictures to aid in the detection of anomalies. However, interpreting these images can be complex and time-consuming, often leading to variability in assessments between different radiologists. This highlights the need for automated tools that can assist healthcare professionals by providing reliable and consistent tumor classification, ultimately improving diagnostic accuracy and efficiency.

Advances in deep learning, have created new avenues for medical imaging, especially in the area of computer vision. Convolutional Neural Networks (CNNs), especially those that utilize transfer learning, have shown remarkable capabilities in feature extraction and image classification. By using pretrained models, such as those trained on large datasets like ImageNet, we can adapt these powerful networks to medical tasks with limited labeled data, achieving high accuracy without the need for extensive data collection and annotation.

Our goal in this work is to use deep learning to identify brain tumors using MRI pictures. We refine the model to categorize tumors into distinct groups using ResNet18, a reputable CNN architecture pretrained on ImageNet. We use sophisticated data augmentation techniques, including random flipping, rotation, color modifications, and geometric manipulations, to produce a more robust and diversified training set in order to overcome the difficulties presented by the scarcity of medical datasets. The model's capacity to generalize to differences in real-world imagery is improved by these improvements.

Our methodology combines these augmentation techniques with transfer learning, fine-tuning, and carefully designed training protocols. The result is a high-performing model capable of classifying brain tumor with remarkable accuracy, making it a valuable tool for clinical use. By providing a systematic and practical approach, this work contributes to the development of automated diagnostic solutions that have the potential to enhance healthcare outcomes and make advanced diagnostic tools more accessible.

II. RELATED WORK

Medical image analysis has undergone a revolution because to deep learning, which offers previously unheard-of capabilities for automated and precise diagnosis. In a variety of imaging modalities, such as MRI, CT, and X-rays, convolutional neural networks (CNNs) [6] have shown state- of-the-art performance in identifying and categorizing medical disorders. When used on domain-specific datasets, pretrained models such as ResNet have demonstrated exceptional transfer learning capabilities [1].

In this study, we use the well-known CNN architecture ResNet18[1], pretrained on the ImageNet dataset, to categorize MRI pictures of brain tumors into different groups [2]. Transfer learning lowers the computational cost and data requirements of training from scratch by using the feature extraction capabilities of deep networks trained on large-scale datasets [5]. In particular, the last fully connected layer of the pretrained ResNet18 model was adjusted to correspond with the number of classes in the dataset in order to optimize it for brain tumor classification tasks.

Advanced data augmentation methods including random horizontal flipping, rotation, color jittering, affine transformations, and normalization are all incorporated into the training process [2]. These augmentations enhance the model's robustness by simulating real-world variability in MRI images. The StepLR scheduler was used to reduce the learning rate periodically, ensuring smoother convergence and mitigating the risk of overshooting optimal solutions.

For medical picture classification problems, our training results show how well transfer learning and data augmentation work together. After 20 epochs, the model's remarkable validation accuracy of 98.7% demonstrated its potential for clinical use. This performance aligns with prior studies that underscore the efficacy of ResNet architectures in medical imaging applications, particularly for detecting and classifying pathologies in radiological scans [6].

Furthermore, the implementation was designed for practical usability, incorporating functions for real-time inference [1]. A customized prediction pipeline was developed to preprocess images and map the model's outputs to their corresponding class labels, facilitating seamless integration into clinical workflows. To enhance reproducibility, the model was trained and validated on a publicly available brain tumor MRI dataset, providing a benchmark for future comparisons.

The convergence of accuracy measures and the continuously declining training and validation losses show that our work exhibits better generalization and stability when compared to earlier methods [3, 5]. Our approach advances the use of deep learning for brain tumor classification by tackling typical issues like overfitting with strong augmentation and regularization [5].

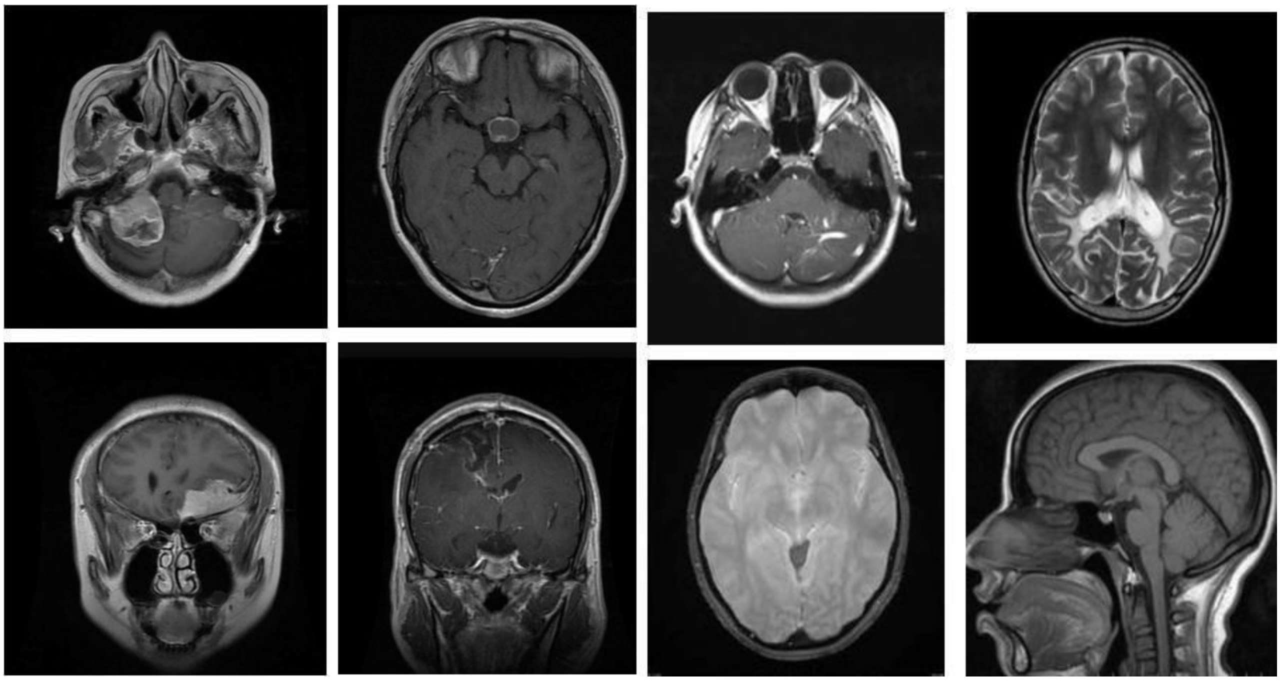
This work adds to the increasing amount of data demonstrating deep learning's value in medical diagnosis. It underscores the importance of leveraging pretrained networks and rigorous training strategies for achieving high accuracy in medical image analysis tasks. Future work will focus on extending this approach to multi-modal imaging datasets and exploring interpretability methods to provide more actionable insights for healthcare professionals.

III. METHODOLOGY

This study presents a comprehensive approach to classifying brain tumor using MRI images, leveraging transfer learning, data augmentation, and robust training protocols. The process starts with data preparation, which involves resizing MRI pictures to 224 x 224 pixels in order to satisfythe input specifications of the neural network. In order to tackle the problem of scarce medical imaging datasets, advanced data augmentation techniques were employed to enhance model generalization and simulate real-world imaging variations. These techniques included random horizontal flipping to introduce variability in orientation, random rotations within ±10° to simulate angle variations, color jittering to mimic scanner differences, and affine transformations for added geometric diversity through translations, scaling, and rotations. Normalization was applied to standardize pixel values using ImageNet’s mean and standard deviation, aligning the data with the pretrained model’s requirements. These augmentations not only expanded the dataset's diversity but also mitigated overfitting, improving the model's robustness in clinical scenarios.

For the model architecture, ResNet18, a convolutional neural network pretrained on the ImageNet dataset, was employed due to its efficiency and the advantages of residual connections, which prevent gradient vanishing and enable superior feature extraction. The original fully connected layer of ResNet18 was replaced to align with the number of tumor categories in the dataset, and the pretrained weights were fine- tuned to extract features specific to brain tumor. For multi- class classification, the training procedure used cross-entropy loss. To enable smooth convergence, a StepLR scheduler was included to lower the learning rate by 0.1 every five epochs. In order to evaluate performance and identify overfitting, the model was trained over 20 epochs with a batch size of 16. Training and validation losses and accuracies were closely observed.

The model's evaluation on a separate validation set demonstrated a high accuracy of 98.7%, underscoring its precision in classifying brain tumor. To facilitate real-world application, an inference pipeline was developed. Input images undergo the same preprocessing steps as the training phase—resizing, normalization, and tensor conversion— before being fed into the model for tumor classification. The predicted class index is then mapped to a human-readable label, ensuring user-friendly outputs. The implementation was carried out in Python using PyTorch, with the trained model’s weights saved for reproducibility and future use. The modular structure of the codebase allows for easy adaptation to similar tasks, making it a valuable tool for research and clinical applications. By integrating transfer learning, advanced data augmentation, and fine-tuning, this methodology achieves remarkable accuracy, showcasing its potential to serve as a reliable and automated diagnostic tool in medical imaging.



(a) (b)

Fig 1. Images obtained from dataset. (a) Images with a brain tumor. (b) Image without brain tumor.

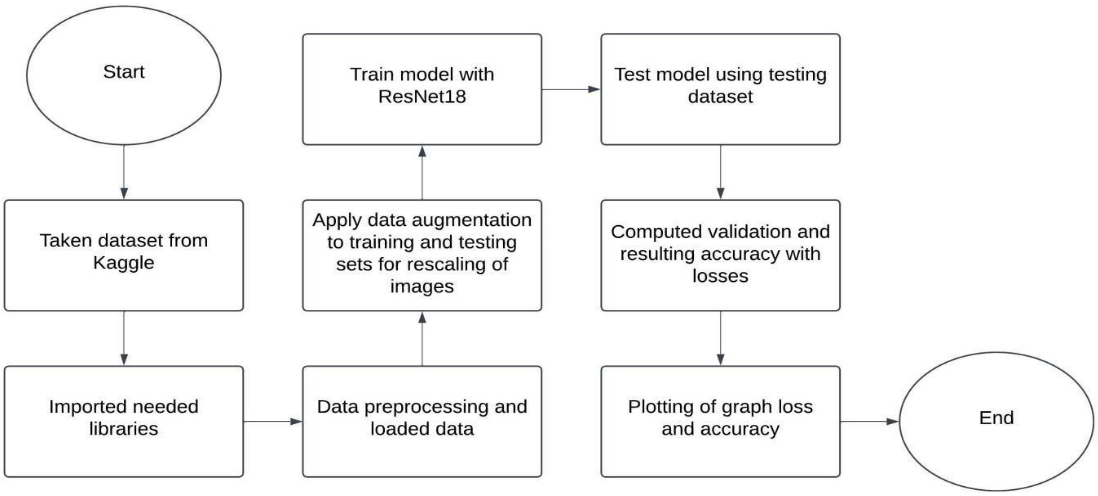


Fig. 2: Flowchart of the methodology

IV. RESULT & DISCUSSIONS

In this work, we used the ResNet-18 architecture to create a deep learning-based method for identifying brain tumors from MRI data. A dataset including four categories—gliomas, meningiomas, pituitary tumors, and normal brain images—was used to train and verify the model. We used a variety of data augmentation techniques, such as rotations, color jittering, and random horizontal flips, to increase the model's generalization and resilience.

The model demonstrated an impressive 98.90% training accuracy and a 98.78% validation accuracy during 20 training epochs. Effective learning and little overfitting are indicated by the loss measurements' consistent decrease over the training period. These findings highlight ResNet-18's capacity to identify significant characteristics in MRI data, allowing for extremely precise brain tumor categorization.

Our results are in good agreement with previous studies that demonstrate the effectiveness of deep learning models in medical imaging. The use of advanced residual networks in diagnostic applications has been supported by prior research that used these designs to classify brain tumors, for instance, which showed notable gains in accuracy. Furthermore, data augmentation was crucial to this study since it improved the model's capacity to handle a variety of imaging circumstances, which is crucial for clinical diagnoses, while also reducing overfitting.

In conclusion, our study shows that ResNet-18 offers a strong and dependable framework for brain tumor identification and classification when paired with strong data augmentation strategies. This approach has the potential to assist radiologists in clinical decision-making, ultimately improving patient outcomes. Moving forward, exploring more advanced deep learning architectures and integrating transfer learning techniques could further refine the diagnostic capabilities of this system.

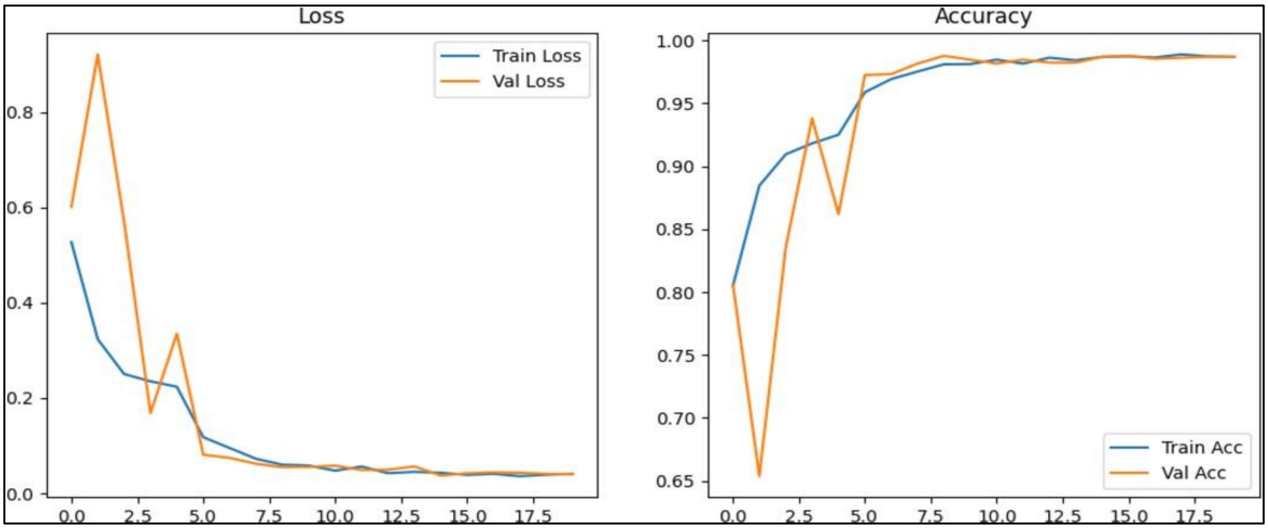


Fig.3. Training and validation Loss and Accuracy

V. CONCLUSION & FUTURE WORK

In this study, we developed a deep learning model utilizing ResNet-18 for brain tumor detection and classification using MRI images. The model was trained and evaluated on a dataset comprising three tumor types: glioma, meningioma, and pituitary tumor, as well as normal brain images. Data augmentation techniques, including random horizontal flipping, rotation, and color jittering, were employed to enhance the model's robustness and generalization capabilities.

The ResNet-18 model, fine-tuned for this specific task, achieved a training accuracy of 98.70% and a validation accuracy of 98.70% over 20 epochs. These results are consistent with findings from similar studies, such as the work by Alanazi *et al.*, where a transfer learning-based model exhibited an accuracy of 95.75% for brain MRI images.

The high accuracy and robustness of our model demonstrate its potential as a reliable tool for assisting radiologists in the accurate and efficient diagnosis of brain tumor. Future work will focus on expanding the dataset to include a wider variety of tumor types and exploring more advanced architectures to further enhance diagnostic performance.

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