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BRAIN TUMOR DETECTION ON DEEP LEARNNG APPROCHES AND MAGNETIC RESONENCE IMAGING

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ABSTRACT

Better treatment outcomes and effective disease management are accomplished by early and accurate diagnosis of brain tumors. See whether deep learning methods can make MRI-based brain tumor detection more precise; that is the primary goal of this study. Our primary objective is to analyze the performance of two popular deep learning architectures, ResNet18 and ResNet34, in identifying and classifying brain tumors from magnetic resonance imaging (MRI) images. In our analysis, we discovered promising results for both models. ResNet18 demonstrates enhanced learning and task adaptation by a steady and consistent increase in accuracy across the training epochs. Conversely, ResNet34 has an initially steeper learning curve, which speeds up its peak accuracy; nevertheless, further research may be required to ascertain its long-term adaptability and stability. By comparing their results to existing best practices, we examine the impact of training duration and hyper parameter tuning on the accuracy of these models. In addition to discussing the study's limitations, we hope to shed light on potential future directions for deep learning research into clinical brain tumor detection and address any further questions or concerns.

Keywords:ResNet18 , ResNet34,(MRI),Convolutional neural network (CNN),YOLO

I. INTRODUCTION

Brain tumors are complex and diverse illnesses, and symptoms, diagnosis, and therapy can be challenging for patients. In order to begin therapies promptly and improve patient outcomes, the ability to diagnose these cancers accurately in their early stages is critical. New medical imaging techniques and the popularity of artificial intelligence (AI) techniques, particularly deep learning, have opened up exciting possibilities for revolutionizing the field of brain tumor detection.

Magnetic resonance imaging (MRI) is an essential technique for detecting and tracking brain cancers due to its multi planar imaging capabilities and improved soft tissue contrast. However, the ability of radiologists and clinicians to decipher magnetic resonance

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imaging (MRI) s can for the presence, kind, and characteristics of tumors is vital. Human analysis is inherently inefficient, subjective, and unpredictable, which might lead to diagnostic errors or treatment delays.

Using deep learning techniques is a very appealing alternative when looking to enhance the accuracy, efficiency, and reliability of MRI-based brain tumor diagnosis. Large and complex datasets have demonstrated deep learning algorithms' exceptional pattern and feature learning capabilities, notably CNNs. Automated MRI scan analysis uses these characteristics to aid in the rapid and accurate detection of brain tumors, giving clinicians more time to decide on a course of therapy.

This research aims to examine the potential of deep learning algorithms created for this specific task utilizing brain magnetic resonance imaging (MRI) images. In this project, we will construct a model that can reliably differentiate between non-neoplastic and tumor regions in brain scans using neural networks. A large and diverse dataset, including several types of tumors, sizes, and locations, is used to train the model to be used in real-world healthcare settings. This ensures the model's ability to adapt to various clinical settings.

A state-of-the-art Convolutional neural network (CNN) architecture, trained and built utilizing state-of-the-art methods, including data augmentation and transfer Learning is trained and built as part of this project to analyze and classify MRI images. Testing the suggested model rigorously using established criteria would assess its accuracy, sensitivity, specificity, and overall performance in comparison to current techniques. If this study's results provide radiologists and clinicians with a reliable method to detect and characterize brain cancers rapidly, it may significantly alter clinical practice. Applying deep learning to medical imaging analysis can enhance neuro-oncology diagnostic accuracy, treatment strategy optimization, and patient care.

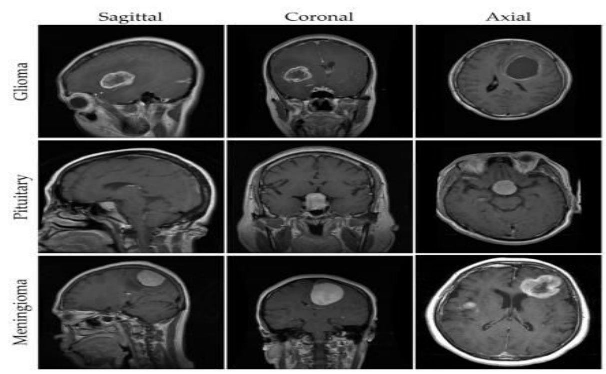

Figure 1. A sample of MRI images from the brain tumor dataset.

II .RELATED WORK

Research into improving brain tumor diagnosis is an important subject, and deep learning techniques have demonstrated potential in this field. The use of deep learning algorithms on magnetic resonance imaging (MRI) scans of the brain has been the subject of several recent research proposals for novel approaches to tumor identification and classification. First-to-market approach for the identification and classification of tiny brain tumors using deep learning [1]. Suggested a strategy for classifying brain tumors that makes use of a combination of deep characteristics and ML classifiers [2]. Offered a method for detecting and classifying brain tumors using deep learning and the YOLO object detection framework [3]. Created an MRI-based hybrid deep learning model for tumor classification and prediction [4]. Shed light on how machine learning may be used to identify brain tumors, leading to more accurate diagnoses and better treatment for patients [5]. Performed an extensive review addressing many facets of utilizing machine learning techniques for the identification and classification of brain tumors.

Huang et al. [12] presented a convolutional neural network (CNN) model that was updated and used for the categorization of brain tumor pictures. With this model, we were able to refine our technique for building neural networks and get excellent classification results. In addition to highlighting the increasing need for automated detection and diagnosis of brain tumors, Mgbejime et al. [13] emphasized the expanding efforts in this area. Kshirsagar et al. [14] demonstrated a new approach to detecting brain malignancies by integrating MRI and artificial neural network methods; their study emphasized the importance of innovative approaches for accurate diagnosis.

Srinidhi et al. [15] used 3D U-net to segment brain tumors and estimate survival rates; this shows that deep learning has great potential for state-of-the-art medical image processing. A degun et al. [16] have shown that deep learning might be used in medical image processing by accurately diagnosing brain tumors through the analysis of magnetic resonance imaging (MRI) data.

Several research covering different parts of brain tumor detection, categorization, and tracking make up the literature review. The necessity for further validation in various clinical contexts was highlighted by Tandel et al. [7], who presented a deep learning-based model that makes use of MRI imaging modalities for the identification of brain tumors. The lack of a comparable evaluation of discriminative and generative models was brought to light by Havaei et al. [8], who utilized deep neural networks to segment brain tumors. The need for standardized methods and clinical validation was highlighted in the literature analysis by Jelski & Mroczko [9] on circulating biomarkers for brain tumor diagnosis.

III METHODOLOGY

Effective treatment planning and patient outcomes depend on precise detection and identification of brain tumors. Medical image analysis using deep learning methods has recently demonstrated encouraging outcomes, especially for MRI-based malignancy identification. Our work, "Enhancing Brain Tumor Diagnosis: Deep Learning Approaches for MRI-Based Detection," sought to increase the accuracy and efficiency of brain tumor detection using MRI images by employing deep learning approaches. This methodology section details the strategy adopted in that study.

Gathering data, cleaning it up, building the model, training it, and finally evaluating it are its essential components. In this section, we lay out the methods used to gather and organize the dataset that underpins our study. Plus, we go into the methods used for

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preparing data to make sure it was suitable for training deep learning models and that it was of high quality.

Our strategy is around creating and using deep learning models that are specifically designed to identify brain tumors. Our investigation centers on the design decisions, hyper parameter tweaking, and optimization techniques used to boost these models' efficiency. In addition, we detail the training procedure, its iterations, and convergence criteria, as well as the data sets used for training, validation, and testing.

To determine the effectiveness and generalizability of the created models, evaluation is essential. Here, we break down the various performance indicators and explain how they work, including AUC-ROC, sensitivity, specificity, and accuracy. We also go over the methods used to look at the findings and understand the model.

In sum, the methodology section gives a thorough rundown of the strategy used in our research, explaining how we created and tested deep learning methods for MRI-based brain tumor identification.

IV ALGORITHM

RESNET18 AND RESNET34

Here we detail how ResNet18 and ResNet34 were chosen as the model architectures for our research. The Residual Networks (or Res Net) are a family of convolutional neural networks well-known for its deep design and exceptional performance across a range of computer vision applications.

One version of the ResNet architecture that has 18 layers is ResNet18. To address the disappearing gradient issue, its architecture is based on residual learning, which involves introducing shortcut connections (also called skip connections) to let gradients flow during training. The training of far deeper networks is made possible by these connections, which enable the network to learn residual functions. ResNet18's design is highlighted by its lightweight nature, which allows it to retain competitive performance. If your computing resources are restricted or you'd rather have a lighter model without drastically reducing performance, it's a good option.

In contrast, ResNet34 is an enhanced version of the ResNet design with 34 layers. In order to facilitate efficient deep network training, it uses residual connections, much to ResNet18. The deeper ResNet34 becomes, though, the more complicated characteristics and representations it is able to glean from the data input.

V IMPLEMENTATION

He et al. 2015 gave the network a name that speaks for what it does: Residual networks or ResNet. The ResNet18 design consists of 72 layers, 18 of which are deep layers. The design of this network was centered on making a lot of convolutional layers operate well together. The concept of jumping connections, sometimes called shortcut connections or identity connections, is central to ResNet. These connections mainly work by creating shortcuts between layers by jumping over one or more of them. With the introduction of these shortcut connections, we hoped to address deep

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networks' most pressing problem: the disappearance of gradient. These shortened links reuse the activations from the prior layer, thereby eliminating the vanishing gradient problem.

At first, these identity mappings do not accomplish much more than reuse activations from earlier layers by skipping connections. The network is compressed throughout this process of ignoring the link, which allows it to learn more quickly. In order for the residual portion of the network to train and explore more feature space, the connections are compressed and then the layers are expanded. A predetermined input size of 224 × 224 × 3 is used by the network. Because of its intricate layered design and the fact that each layer receives data from and sends data to other levels, the network is classified as a directed acyclic graph (DAG) network.

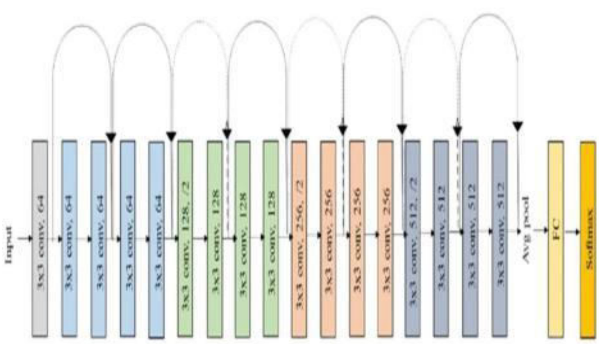
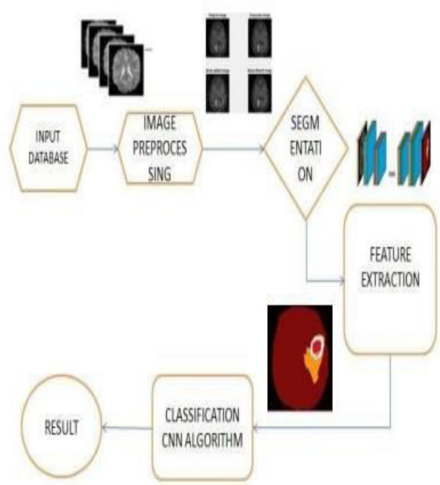


Fig5. ResNet18 Architecture

TRAINING PROCESS

The data used to train the ResNet18 and ResNet34 models is the labeled dataset, which consists of pictures marked as either having tumors (positive label) or not having any tumors (negative label). The algorithms learn to distinguish between tumor and non-tumor tissues by repeatedly analyzing the pictures for complex patterns and characteristics.

Because pictures contain a wide variety of variations in size, contrast, and intensity, image pre-processing is crucial for a smooth and efficient training process. Optimizing input photos through a sequence of operations is the first stage in pre- processing; the first of these techniques is wrapping and cropping. With order to wrap, the input picture must be evaluated with respect to the boundaries of the primary object. At this stage, we want to make sure the picture borders are sharp and that the focal point is in the exact middle of the frame. After that, the image is cropped so that just the important parts can be shown, making it better for further analysis and training the model.



Overview for Brain Tumor Detection Using ResNet18 and ResNet34 Models

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VI .RESULTS

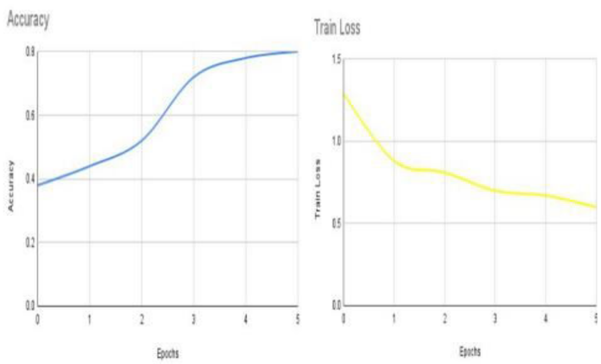

Fig-6.1.1 Resnet18 Accuracy And Train Loss

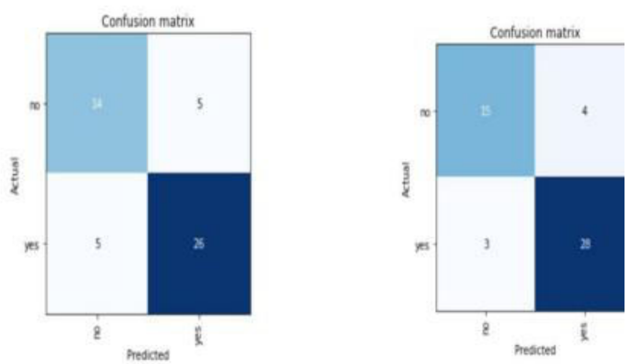

Fig- 6.1.2Confusion Matrix of Resnet 18 and Resnet34

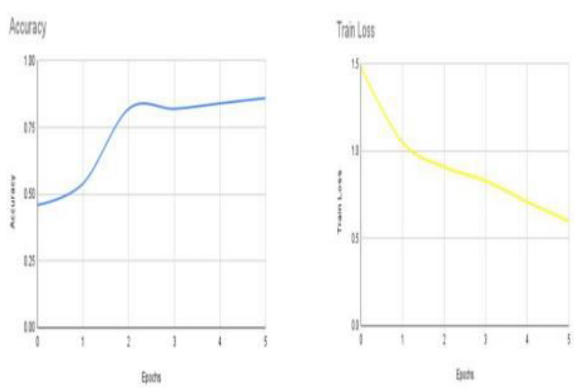

Fig- 6.1.3Res Net34 Accuracy and Train Loss

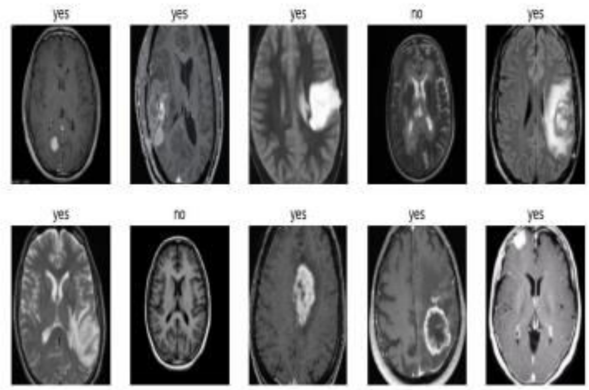

Fig- 6.4 Different pictures

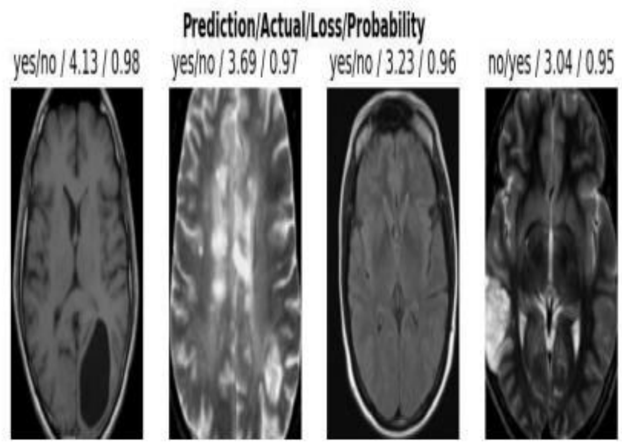

Fig:6.5 Prediction

VII CONCLUSION

This research looked at how well deep learning models, namely ResNet18aResNet34, could identify brain cancers in magnetic resonance imaging (MRI) scans. These models were trained and evaluated using a dataset of 253 pictures, which included cases with and without tumors. The results showed encouraging performance, with ResNet34 obtaining an average accuracy of 86% on the training data, which is somewhat better than ResNet18's 80%. These results highlight the promise of these deep learning structures for reliably identifying brain tissues affected by tumors, demonstrating their usefulness in assisting doctors with rapid and accurate tumor detection. Clinical practice stands to benefit greatly from this study's findings, as MRI scans may be used to accurately diagnose brain cancers. As far as using AI-driven methods to improve diagnostics goes, ResNet18 and ResNet34 represent a huge step forward. With the use of these models, neuro-oncology patients may benefit from early therapies and better results because to more precise tumor diagnosis. Improving the precision and usefulness of these models in practical clinical contexts would need recognizing the study's shortcomings and thinking about potential future research paths, such expanding deep learning architectures and diversifying datasets.

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