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MRI BASED BRAIN TUMOR DETECTION USING DEEP LEARNING

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Abstract:
Patient outcomes are greatly impacted by brain tumor detection, which is essential for early diagnosis and treatment planning. By evaluating magnetic resonance imaging (MRI) images and other medical imaging data, deep learning systems have demonstrated encouraging results in automating this process. An extensive evaluation of current developments in deep learning-based techniques for brain tumor identification is provided in this work. It covers a number of topics, such as network structures, training methods, assessment metrics, and data pre-processing. In order to give researchers and doctors working towards more precise and effective brain tumor detection systems some insight, it also addresses issues and potential future paths in the field.

The early identification and successful treatment planning of brain tumors depend on their detection. Deep learning methods, namely those that analyses magnetic resonance imaging (MRI) scan data, have demonstrated promise in automating this process. Recent developments in deep learning-based techniques for brain tumor identification are reviewed in this publication. Training methodologies, network designs, evaluation metrics, and data pretreatment are just a few of the topics it covers. Convolutional neural networks (CNNs), one type of deep learning algorithm, have proven to be exceptionally effective at identifying and localizing brain tumors based on their ability to discern intricate patterns from magnetic resonance imaging. Prospective paths are explored and issues like data scarcity, interpretability of the model, and generalization to different populations are tackled. To further enhance the area and advance patient care, collaboration between researchers, physicians, and industry players is

Keywords –
MR Images, Brain Tumor, Convolution Neural Networks (CNN), Image recognition, Deep learning, VGG-16, RESNET-50.

I.INTRODUCTION

Because of their high rates of morbidity and mortality,brain tumors pose a serious worldwide health concern. For optimal treatment planning and better patient outcomes, brain tumors must be identified early and accurately. A key component in the identification and characterization of brain tumors is medical imaging, namely magnetic resonance imaging (MRI). Diagnosis and treatment commencement may be delayed, though, as MRI scan interpretation is a skillful and time-consuming process. With the advent of deep learning algorithms, medical image analysis has gained strength and can now detect brain tumors automatically and effectively. In a variety of medical imaging tasks, such as brain tumor identification, segmentation, and classification, deep learning models—like convolutional neural networks (CNNs)—have shown impressive performance. By utilizing hierarchical features and big datasets

Convolutional neural network (CNN) architectures ResNet-50 and VGG-16 are two well-known models that have significantly advanced the fields of deep learning and computer vision. For a variety of applications, including feature extraction, object identification, and picture classification, these models are extensively utilized. Both VGG-16 and ResNet-50 are extensively employed as feature extractors or as the foundation architecture for transfer learning across several domains because they have been pre-trained on extensive picture datasets like ImageNet. Although ResNet-50 addresses the difficulties of training very deep neural networks, VGG-16 offers a straightforward and easily understood design. This leads to an improvement in training efficiency and performance. In addition to inspiring many later designs and developments, these models are still used as industry standards in the field of deep learning.

II.PROPOSED WORK

In order to automatically detect Brain Tumor, our method makes use of cutting edge deep learning approaches. In order to recognise patterns in photos, we employ Convolutional Neural Networks (CNN), which function similarly to sophisticated computer algorithms as shown in figure 3.1

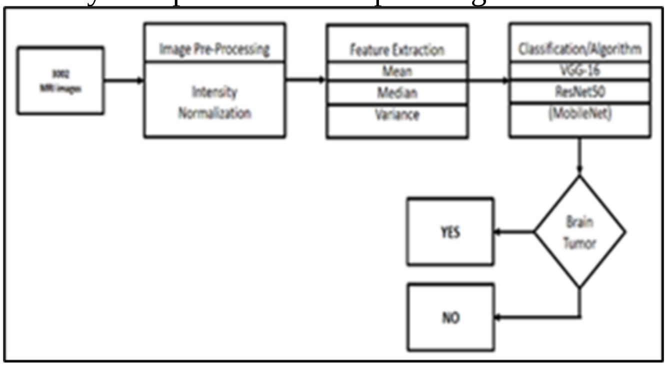

Figure 1. PROPOSED SYSTEM

❖ *Dataset/Data Collection*

Brain Tumor MRI Image Dataset contain 3002 images which Available from kaggle Website. Dataset is further divided into two types: Yes and No Each Folder contain 1500 Brain tumor images which can be used for Training, Testing and Validation purpose. Also 2 Brain images (Tumor and Normal Brain) are using as a Sample Testing Instance.

❖ *Data augmentation*

Our dataset was small and only included MR images, but deep neural networks require a large dataset to produce promising results. Our dataset included a total of 3264 MR images, with 80% of the data used for training and the remaining images used for testing and validation at a rate of 10% and 10%, respectively. The amount of the original data can be increased by augmentation, and then, the training can be improved. Additionally, this enhances the model’s capacity for learning. Therefore, we performed data augmentation by mirroring the MR images and applied rotation, width and height shifting, and zooming. The datasets were then validated using the holdout validation method

❖ *Data pre-processing*

Data pre-Processing is a crucial step in data analysis that involves grayscale conversion, Intensity Normalization, Cropping, Resizing, shaping, Noise Reduction, etc. IMG to RGB conversion and intensity Normalization done in this step automatically as these features are in-built in CNN model.

❖ *Feature Extraction*

It is the process by which certain features of interest in an image are detected and presented for further processing. When extracting, certain parameters are taken into account: size, shape, composition,

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image location. This step extracts the features of the given input image. Based on these characteristics, the image is analyzed and the area of the tumor is determined. Mean, Median, Variance are some mathematical Concepts use for Feature Extraction.

❖ ***Model Architecture***

In our study, an input image with a size of 32 × 32 pixels was sent to an initial convolutional layer with 16 filters, a 32 × 32 × 16 feature map, and a kernel size of 3 × 3 in order to search for the most-generic features. The convolutional layer's output was then forwarded to a max-pooling layer feature map of 15 × 15 × 16 to decrease the size of the spatial data for the subsequent layer by half.

The max-pooling procedure selected the greatest number of elements or pixels from the feature map area that the filter has covered. This result was then fed to a further convolutional layer with filter values of 32 and a 13 × 13 × 32 feature map with a 3 × 3 kernel size. After that, the output was then forwarded to the max-pooling layer feature map of 6 × 6 × 32 to cut the amount of spatial data for the next layer in half. Another convolutional layer and another pooling layer came next.

The feature map of 4 × 4 × 64 in size was made up of 64 filter values and a kernel size of 3 × 3 in the final convolutional layer, while the final pooling layer had a feature map of 2 × 2 × 64 . The newly created 4160-dimensional fully connected dense layer received the flattened final output of the previous convolutional layer. This output was sent to the final output layer. All the other layers utilized a dropout of 0.5 with a ReLU activation function. The above-proposed CNN architecture's configuration is depicted in Figure 2. The model was trained, validated, and tested using 80 epochs, a batch size of 18, and a learning rate of 0.01. Along with the Adam optimizer, a categorical cross-entropy-based loss function was calculated to find the loss value.

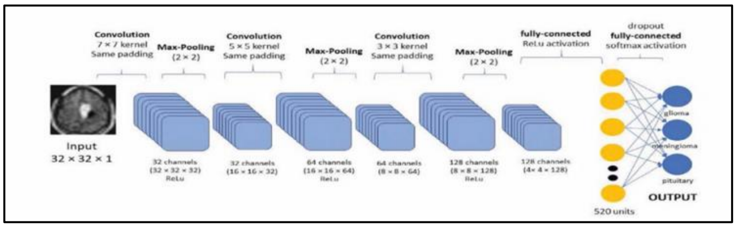

Figure 2 .CNN ARCHITECTURE

III.CLASSIFIER/ALGORITHMS –VGG-16:

VGG16 is a deeper network for detecting and classifying images.it performs better when dealing with vast amounts of data and in complex context recognition tasks. The VGG16 network includes 16 convolutional layers and a 3 by 3 receptive field. There are a total of 5 such layers, each with a size of 2 2 (max-pooling layers). The final max-pooling layer is followed by 3 completely linked layers. The ReLU activation function is utilized to activate the hidden layer in VGG16, and the final layers use the softmax classifier

ResNet50: The short form of the residual network is ResNet-50. ResNet-50 is an adaptation of the ResNet architecture that has 50 deep layers and has been trained using at least one million examples from the ImageNet database The ResNet-50 architecture comprises a series of average pooling convolutional units. If there is a large amount of data accessible and there are more layers and parameters, the accuracy will increase. However, when the number of parameters or layers increases, issues such as vanishing gradients start to occur. At this moment, residual networks operate more effectively and provide good solutions.

CNN: CNN stands for Convolutional Neural Networks which is a type of Deep Learning Algorithm commonly used for image recognition and classification tasks. It works by using a series of convolution layer to automatically learn feature from input images, follow by pooling layer to reduce the dimensionality and fully connected layers for classification. CNN have been incredibly successful in various applications like object detection, Facial Recognition and medical image analysis

IV.LITERATURE REVIEW

An approach introducing a machine learning-based strategy for the automated identification and classification of Brain Tumor has been developed by Ahmed, Kosrat Dlshad and colleagues Using a standardized testing strategy on the 3064 brain MRI images which available on Figshare, Zarin Anjuman Sejuti, Md Saiful Islam [1] performed a comparative examination of deep learning-based brain tumour notification models using CNN, SVM. An Accuracy of 97.1% was achieved across various tumour subtypes, indicating that ensemble models outperformed single-network structures.Md Ishtyaq Mahmud, Muntasir Mamun and Ahmed Abdelgawad [2] Published an Article on" (2023) in which They used Transfer learning models such as CNN, Resnet-50, VGG-16, Inception-V3 to detect brain tumour precisely from the dataset of 3264 MRI images having Accuracy of 93.30%, AUC of 98.43%, recall of 91.13%, and loss of 0.25.Shahzad Ahmad Qureshi,Shan E Ahmed Raza,Lal hussain,Areej A Malibari,Mohamed k Nour,Aziz ul Rehman,Fahd N Al-Wesabi,Anwer Mustafa Hilal [3]created a model that employs a variety of classifiers including SVM kernel ,KNN, RF, to predict Brain Tumor (BT). Their study outperformed earlier efforts with an average validation accuracy of 97.20%.Rajat Mehrotra, M. A. Ansari, Rajeev Agrawal, R.S. Anand [4] used transfer learning on brain MRIs to develop a model that could classify pictures by implementing techniques like AlexNet, GoogleNet, SqueezNet, ResNet Architecture. The model outperformed earlier techniques, with a validation accuracy of 94.74%. In order to distinguish between Tumour and normal brain images.Md. Saikat Islam Khana, Anichur Rahman, Tanoy Debnatha, Md. Razaul Karima, Mostofa Kamal Nasira, Shahab S. Band, Amir Mosavi , Iman Dehzang[5]Created a model to forecast the phases of Brain Tumor disease using convolutional neural networks and deep feature-based techniques. This model outperformed earlier methods with an astounding accuracy rate of 97.80%.N. Sravanthi, Nagari Swetha, Poreddy Rupa Devi, Siliveru Rachana, Suwarna Gothane, N. Sateesh[6] research addressed issues including the necessity for a large number of training images and the optimisation of deep network topologies in order to diagnose Brain Tumour disease using MRI data using transfer learning.Md Khairul Islam,Md Shahin Alia,Md Sipon Miah, Md Mahbubur Rahman, Md Shahariar Alam, Mohammad Amza Hossain[7] Validated the usefulness of these characteristics for clinical categorization by choosing additional individuals based on baseline data and critical qualities for Tumour identification. By comparing samples of healthy and afflicted brain tissue, Confirmed the diagnosis of BT.Heba Mohsen,El-Sayed A.El-Dahshan, El-Sayed M. El-Horbaty, Abdel-Badeeh M. Salem.[8] Created a model to forecast the phases of Brain Tumor disease using convolutional neural networks and deep feature-based techniques. This model outperformed earlier methods with an astounding accuracy rate of 86.97% Disha Sushant Wankhede, R. Selvarani,.[9] developed a model that combines machine learning and Grey Wolf Optimization R-CNN, In terms of diagnosing late-onset BT, their model showed an 62.54% sensitivity, 77% specificity, and 95% overall accuracy.By extracting MRI features to accurately predict the diagnosis of BT, Priyanka Rawat [10] Investigated the analysis of BT data using deep convolutional autoencoder with 88.88% sensitivity, 91.78% specificity, and 91% overall accuracy.Saurabh Kumar, Iram Abid, Shubhi Garg, Anand Kumar Singh, Vivek Jain[11] Assessed the diagnostic capability of MRI images in identifying stages of motor cognitive impairment, using tagged MRI characteristics to improve diagnostic precision of Brain Tumor having 81% sensitivity, 97% specificity, and 89.7% overall accuracy.Raphael M. Kronberg, Dziugas Meskelevicius, Michael Sabel, Markus Kollmann, Christian Rubbert, Igor Fischer [12] stressed the critical importance that an accurate BT diagnosis plays in early management. With less labelled training data, Zhang and Wang's[13] deep learning architecture improved performance with encoder-decoder based CNN architecture 2D-CNN Auto encoder were used by Soheila Saeedi, Sorayya Rezayi, Hamidreza Keshavarz and Sharareh R. Niakan Kalhor. To improve classification accuracy in medical research, leading to high precision in BT diagnosis and the differentiation of healthy from Brain Tumor patterns.In their exploration of machine learning techniques for the categorization of BT according to classification, D. Rammurthya, P.K. Mahesh[14] Using SimBRATS 2014 Dataset by performing techniques like WHHO-based Deep CNN, Were able to identify between groups with high accuracy rates with 79.1% sensitivity, 97.4% specificity, and 81.6% overall accuracy.Wozniak et al.[15] developed a cutting-edge correlation learning method (CLM) for deep neural network structures that integrates the CNN with a conventional architecture. Meningioma (708 images), glioma (1426 images), and pituitary (930 images) tumors were among the 3064 brain cancers they investigated. Their designed CLM model had an accuracy of around 96%, a precision of about 95%, and a recall of about 95%.Amjad Rehmanetal.[16] introduced a deep learning-based approach to detect and characterize microscopic brain tumours. The first step consists of designing a 3D convolutional neural network (CNN) architecture, Using the correlation-based selection method, the extracted features are transferred to this method, and as an output, the best features are selected. Experimental and validation studies were conducted with three BraTS datasets (2015, 2017, and 2018), and the accuracy was 98.32, 96.97, and 92.67% respectively.Sajjad et al.[17] designed a CNN-based multi grade brain tumor classification model for detecting the regions of tumor present in the brain MRI. the regions of the tumors present in the MR image were segmented using the deep learning method. pre-trained CNN model undergoes fine-tuning for classifying the severity of brain tumors. The method showed enhanced performance but failed to balance the efficiency and accuracy simultaneously.Gumaei et al[18] introduced an automated approach to assist radiologists and physicians in identifying different types of brain tumors.brain image preprocessing, brain feature extraction, and brain tumor classification.The dataset provided by Cheng was used by the researchers in their study and consisted of 3064 MRI images from 233 patients a fivefold cross-validation method was utilized. The results reported 94.23% accuracy.Rajeshwari G tayade et.al [19] in their paper they gave a mixture of wavelet statistical features and co-occurrence wavelet texture feature obtained from two level distinct riffle remodel. A grouping of WST and WCT was used for feature extraction of neoplasm region extracted from second level separate ripple remodel.Sunanda D.[20] proposed a classifier method using convolutional neural network where some morphological operation was used and resize, filtering, equalize, and histogram analysis were done. The average accuracy of the proposed work is 94.39%.

V.CONCLUSION

Brain tumor detection using deep learning has shownpromising results in recent studies. Deep convolutional neural networks have been proposed to diagnose binary and multiclass brain tumors with high accuracy. These models utilize Magnetic Resonance Imaging (MRI) to detect and classify tumors . The use of deep learning techniques has improved the accuracy of brain tumor detection, and it has the potential to aid in early diagnosis and treatment. However, there are still challenges to be addressed, such as the need for large datasets and the development of more robust models.It has the potential to revolutionize the field of medical imaging. With further research and development, these models can become a valuable tool for radiologists and clinicians in diagnosing and treating brain tumors

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