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Deep Learning Approach For Brain Tumor Segmentation and Anomaly Detection

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Abstract: In recent years, there has been a surge of interest in the healthcare research community for AI to help with big data analytic and decision-making. One of the primary reasons for this is the massive influence of deep learning on the use of complicated healthcare data. The main goal here is to identify brain tumors and brain bleeding by means of deep learning and improve care for those who are suffering. Tumors are the term used to describe abnormal cell growths in the brain, while cancer is the term used to describe malignant tumors. Brain cancer regions are typically discovered via CT or MRI imaging. For the detection of brain tumors, there are certain methods. These include molecular testing, lumbar puncture, cerebral angiogram, and positron emission tomography (PET scan or PET-CT scan). This study analyses the illness state using data or images from an MRI scan. The goals of this research are to (i) segment the tumor region and (ii) identify the abnormal image. The segmented mask can be used to evaluate the tumor's density, which will aid in treating the tumor in the easiest and fastest way possible given the data collected. A deep learning algorithm is used to analyze MRI pictures and find anomalies. Multi-level thresholding is used to divide the tumor region for analysis. The quantity of cancerous pixels indicates the density of the afflicted area.

Index Terms* - *Brain Tumor, Magnetic Resonance Imaging (MRI), Residual Network (ResNet), Convolutional Neural Networks (CNN), Deep Learning.

I. INTRODUCTION

Brain tumors are one of the most aggressive diseases, affecting both infants and adults. Brain tumors proliferate rapidly, and the patient's chances of survival are very poorif they are not properly treated. Early detection of brain tumors is essential. Proper therapy planning and accurate diagnostics are crucial for extending patient lives. Magnetic resonance imaging is the most reliable technique for locating brain tumors. The doctor looks over the images fromthe MRI. Because of the complexity of brain tumor and their characteristics, manual examination might be error- prone. Consequently, a brain tumor detection system that is automated is required to identify cancers at their earliest stage.

To identify the tumor based on MRI images, the proposed study applies deep learning techniques with Depth wise separable Convolution Neural Network. A deep learning method defines low-level categories like letters first, then slightly higher-level categories like words, and then higher-level categories like sentences. These categories are learned incrementally through the hidden layer architecture. In order to recognize faces in images, image identification first involves classifying lines and then shapes by lightness and darkness.

Traditional machine learning techniques require a subject expert to identify the majority of the applied features in order to simplify the data and make patterns more apparentto the learning algorithms. The main benefit of deep learning algorithms, as previously discussed, is that they attempt to incrementally acquire high-level features from data. This eliminates the need of domain knowledge and hard-core feature extraction.

We suggest the well-known ResNet algorithm, which is based on Convolutional Neural Network design and typically requires more training time than traditional machine learning algorithms but significantly less testing time than traditional machine learning models.

II. LITERATURE SURVEY

Machine learning and deep learning approaches in detectingfour brain diseases such as Alzheimer's disease, brain tumor, epilepsy, and Parkinson's disease. Twenty-two datasets are discussed and feature extraction techniques are discussed. Key findings from the reviewed articles are summarized and major issues related to machine learning/deep learning-based brain disease diagnostic approaches are discussed. Through this study, the most accurate technique for detecting different brain diseases can be employed for future betterment. [1]

The use of computer-assisted techniques to classify brain tumor images without human intervention. Traditional andhybrid ML models were built and analyzed, 16 different transfer learning models were also analyzed, and a stacked classifier was proposed. The proposed VGG-SCNet's precision, recall, and f1 scores were found to be 99.2%, 99.1%, and 99.2% respectively. [2]

An ensemble of two segmentation networks: a 3D CNN and a U-Net. Both models were trained on the BraTS-19 challenge dataset and evaluated to yield segmentation maps which differed from each other in terms of segmented tumor sub-regions. The suggested ensemble achieved dice scores of 0.750, 0.906 and 0.846 for enhancing tumor, whole tumor, and tumor core, respectively, on the validation set, performing favorably in comparison to the state-of-the-art architectures. [3]

Convolutional neural network and MRI detection technology to construct a model adapted to brain tumor feature detection. The main function of the model is to segment and recognize MRI brain tumors and use convolutional layers to improve recognition efficiency and rate. It also uses feature fusion to further improve the diagnostic results. The research shows that the model algorithm has practical effects and can provide theoretical reference for subsequent related research. [4]

The application of deep learning models for the identification of brain tumors. Two scenarios were assessed: pre-trained Den-sNet201 deep learning model and SoftMax classifier. The ensemble method based on con-catenation of dense blocks by using DensNet201 pre-trained model outperformed the current research methods for brain tumor classification problem. The proposed method produced 99.51% testing accuracy on testing samples and achieved the highest performance in detection of brain tumors. Future research will explore fine-tune and scratch-based features extracted from deep learning models. [5]

The DWA-DNN classifier has achieved a great result in terms of accuracy, specificity, sensitivity and other performance measures when compared to existing classifiers. The results show that its accuracy and statistical measure is far more competing than other non-deep learning techniques. It would be interesting to explore the possibility of combining the DNN with other variations of the autoencoder to see the effect or performance in the same brain MRI dataset. [6]

MRI is commonly used to detect brain tumors due to its superior image quality and no ionizing radiation. This paper proposes a DL model based on a convolutional neural network to classify different brain tumor types using two publicly available datasets, achieving the best overall accuracy of 96.13% and 98.7%. The results indicate the ability of the model for brain tumor multi-classification purposes. [7]

Brain tumor segmentation method based on multi- cascaded convolutional neural network (MCCNN) and fully connected conditional random fields (CRFs). The process involves combining intermediate results of several connected components, applying CRFs to consider spatial contextual information, and using image patches from axial, coronal, and sagittal views to train three segmentation models and combine them to obtain the final segmentation result. [8]

An automated approach for brain tumor detection that includes enhancement at the initial stage to minimize gray- scale color variations. Filter operation was used to remove unwanted noises, threshold-based OTSU segmentation was used instead of color segmentation, and pathology expertsprovided feature information to identify the region of interests.The experimental results showed that the proposed approach was able to perform better results while maintaining the pathology experts' acceptable accuracy rate. [9]

A combination of multimodal information fusion and convolution neural network detection method of brain tumors. It uses the extension of the 2D-CNNs to multimodal 3D-CNNS, and can obtain brain lesions under different modal characteristics of three-dimensional space. A real normalization layer is added between the convolution layers and pooling layer to improve convergence speeds and alleviatethe problem of overfitting. The experimental results showed that the brain tumor detection method could effectively locate tumor lesions, and better results were obtained in correlation coefficient, sensitivity, and specificity. Compared with two-dimensional detection networks and single modebrain tumor detection methods, the detection accuracy is significantly improved. [10]

A CNN-SVM optimization model and proposes a braintumor benign and malignant identification algorithm basedon this model. Experimental results show that the algorithm has high robustness and accuracy, and is not prone to missed malignancy. The overall performance of the algorithm is betterthan the traditional CNN model using SoftMax classifier. [11]

An approach to diagnosing brain hemorrhage by using deep learning. Three types of convolutional neural networks, LeNet, GoogLeNet, and Inception-ResNet, are employed. We built a dataset of 100 cases collected from the 115 Hospital, Ho Chi Minh City, Vietnam. The experimental results show that the three networks achieve accuracy of 0.997, 0.982, and 0.992 respectively on the dataset. We found that convolutionalneural networks are pre-trained with non-medical images and can be used in medical image diagnosis, particularly in brain hemorrhage diagnosis. LeNet is the most time-consuming model. [12]

Automatic tumor detection process plays the major actionto help for increasing the treatment possibilities. Proposedstrategy utilizes spatial domain technique for delivering the quality picture. The CNN technique additionally identifies the location pertaining to the brain as well as the territory of the tumor in the brain. from the MRI images. tissues and tumor tissues. [13]

An automatic segmentation method based on ConvolutionalNeural Networks (CNN), exploring small 3 3kernels. It was validated in the Brain Tumor Segmentation Challenge 2013 database, obtaining the first position for the complete, core, and enhancing regions in Dice Similarity Coefficient metric. Intensity normalization as a pre-processing step proved tobe effective for brain tumor segmentation in MRI images. [14]

A technique for detecting the tumor commencing the brain MR images. They also worked on different techniques, which include pulse-coupled Neural Network and noise removal strategies for reinforcing the mind MRI images and backpropagation network for classifying the brain MRI images from tumor cells. They observed image enhancement and segmentation of the usage of their proposed technique, and the backpropagation network helps in the identification of a tumor in a brain MR image. [15]

A generative approach for simultaneously registering a probabilistic atlas of a healthy population to brain magnetic resonance (MR) scans showing glioma and segmentingthe scans into tumor as well as healthy tissue labels. Theproposed method is based on the expectation maximization (EM) algorithm that incorporates a glioma growth model for atlas seeding, a process which modifies the original atlas into one with tumor and edema adapted to best match a given set of patient's images. The method is validated by automatically segmenting 10 MR scans and comparing the results to those produced by clinical experts and two state-of-the-art methods. We additionally apply the method to 122 patients scans and report the estimated tumor model parameters and their relationships with segmentation and registration results. Based on the results, we construct a statistical atlas of the glioma by inverting the estimated deformation fields to warp the tumor segmentation of patients scans into a common space. [16]

In order to identify brain tumors in MRI pictures of cancer patients, image processing techniques such histogram equalization, image segmentation, image enhancement, morphological procedures, and feature extraction have been developed. Gray Level Co-occurrence Matrix was used to derive textural information from the discovered tumor (GLCM). To identify various forms of brain cancer,a neurofuzzy classifier has been created. Two testing phases—the learning/training phase and the recognition/testingphase—have been conducted on the system. The approachwas tested using known MRI pictures of individuals withbrain cancer that were collected from Tata Memorial Hospital (TMH) and unknown samples of impacted MRI images that were also obtained from TMH. [17]

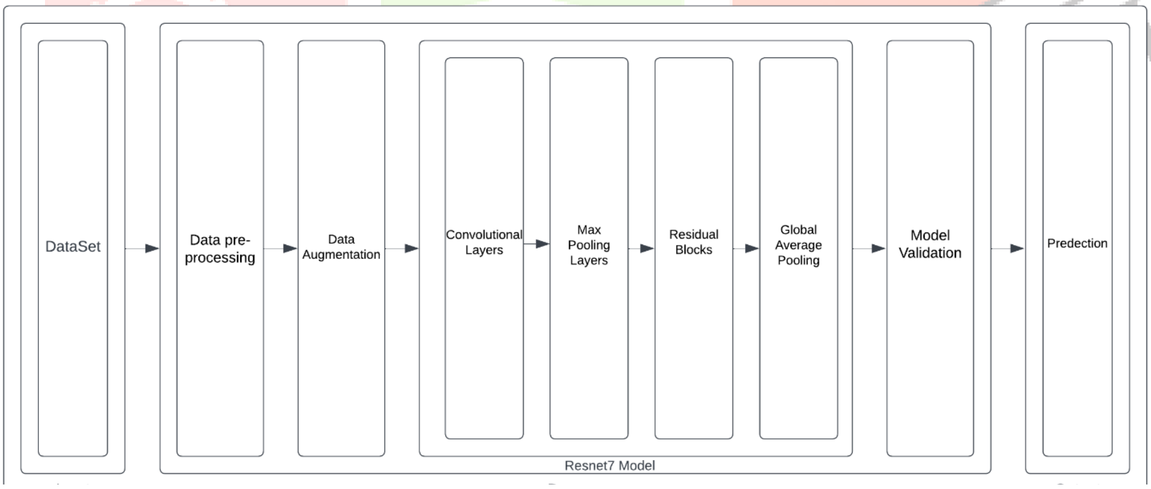
III. PROPOSED APPROACH

The proposed approach uses Deep neural networks in order to get the best model as a result. Convolutional neural net- works (CNN), such as the ResNet model, is an effective modelfor image classification in CNN But their use can be hindered by the challenge of selecting appropriate hyperparameters. Thenumber of residual blocks, filters, and activation functionsmust be carefully chosen to achieve optimal performance and avoid overfitting or slow convergence. And now we will aboutthe ResNet module.

ResNet7:

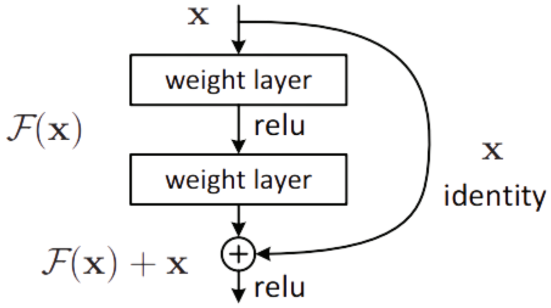
The ResNet architecture is based on the concept of residual blocks. In each residual block, the input is first passed through one or more convolutional layers with learnable parameters, followed by a shortcut connection that adds the input back to the output of the convolutional layers. Thisallows the network to learn residual representations of theinput, making it easier to optimize and reducing the risk of vanishing gradients.

In the ResNet7 variant, the number of residual blocks has been reduced to 7. The kernel size of the convolutional layers has been increased and the number of filters is increased every other block by a factor of 2. This results in a shallower network with reduced complexity, while still taking advantageof the residual connections. The architecture also includessubsampling of the input by a factor of 2 every other block, which reduces the spatial resolution of the activations, andthe use of a dropout rate of 0.55, which helps to prevent overfitting.



Block Diagram

The working of a ResNet-7 model is based on the concept ofresidual connections. In this architecture, each layer receives input from the previous layer, processes it, and passes the result to the next layer. Additionally, the input to each layer is also added to its output, bypassing the processing done by thatlayer. This allows the model to learn the residual or differencebetween the input and the desired output, instead of trying to learn the entire mapping from input to output.



ReLU Block

The model uses convolutional layers to extract features from the input image and uses fully connected layers to produce the final classification. The activation function usedin the layers is usually ReLU (rectified linear unit), which helps to introduce non-linearity into the model.

The backpropagation algorithm is used to update the model parameters during training. During the forward pass, the model computes the output for a given input, and during the backward pass, the gradients of the loss with respect tothe model parameters are computed and used to update the parameters. This process is repeated multiple times for a large number of input images to train the model.

Once the model is trained, it can be used for making predictions on new, unseen images. The input image is passed through the network, and the output of the final layer providesthe predicted class label for the image.

IV. CONCLUSION

After reviewing the literature, it can be said that utilizingthe ResNet7 model to identify brain tumors is a promising strategy with a significant amount of potential. A deep convolutional neural network known as ResNet7 has beenextensively employed in medical imaging to identify different tumor types, including brain tumors.

Research have demonstrated that the ResNet7 model can diagnose brain cancers with high accuracy from a varietyof imaging modalities, such as magnetic resonance imaging (MRI) and computed tomography (CT). Early tumor detectionhas been found to be greatly assisted by its capacity to captureminute alterations in brain pictures, which improves patient outcomes.

Moreover, the ResNet7 model's architecture allows for easy customization and adaptation to different imagingmodalities, enhancing its versatility in clinical practice. The model's efficiency and reliability make it a valuable tool for medical professionals in diagnosing and treating brain tumors.

In conclusion, the use of the ResNet7 model for identifying brain tumors is a promising approach that has shownsignificant potential in improving the accuracy and efficiency of medical imaging. Further studies are needed to validateits effectiveness and explore its clinical applications, but itis clear that the ResNet7 model has the potential to be avaluable asset in the fight against brain tumors.

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