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Brain Tumor Classification (MRI) Using Deep Learning

Dr.K.Sharmila[1], Dr.R.Devi[2]

Professor, Department of Applied Computing and Emerging Technologies, VISTAS, India[1]

Professor, Department of Applied Computing and Emerging Technologies, VISTAS, India[2]

ABSTRACT: A Brain tumor is considered as one of the aggressive diseases, among children and adults. Brain tumors account for 85 to 90 percent of all primary Central Nervous System(CNS) tumors. Every year,around 11,700 people are diagnosed with a brain tumor. The 5-year survival rate for people with a cancerous brain or CNS tumor is approximately 34 percent for men and36 percent for women. Brain Tumors are classified as: Benign Tumor, Malignant Tumor, Pituitary Tumor, etc. Proper treatment, planning, and accurate diagnostics should be implemented to improve the life expectancy of the patients. The best technique to detect brain tumors is Magnetic Resonance Imaging (MRI). A huge amount of image data is generated through the scans. These images are examined by the radiologist. A manual examination can be error-prone due to the level of complexities involved in brain tumors and their properties. Application of automated classification techniques using Machine Learning (ML) and Artificial Intelligence (AI) has consistently shown higher accuracy than manual classification. Hence, proposing a system performing detection and classification by using Deep Learning Algorithms using Convolution Neural Network (CNN), Artificial Neural Network (ANN), and Transfer Learning (TL) would be helpful to doctors all around the world.

KEYWORD: Brain tumor, Magnetic Resonance Imaging (MRI), Convolution Neural Network (CNN), Artificial Neural Network (ANN), and Transfer Learning (TL).

I. INTRODUCTION

Brain tumor detection is a crucial component of medical imaging and is crucial to the diagnosisandmanagementofillnessesassociatedwiththebrain.Themanualexamination of medical pictures used in conventional techniques of tumor identification can be time- consuming and proneto human error [1].However, the quick development of deep learning methods, particularly in the area of computer vision, has created new opportunities for the automatic and precise diagnosis of brain tumors [2]. Convolutional neural networks (CNNs), a type of deep learning algorithm, have displayed astounding performance in image analysis tasks including object detection and segmentation [3]. Researchers have been investigating the possibility of these methods for identifying and categorizing brain tumor's from magnetic resonance imaging (MRI) data by using the capabilities of deep learning [4].

Researchers are putting in a lot of effort to build CNNs that can properly identify and classify brain tumor, as well as other forms of medical imaging, in order to enhance the medical diagnostic and treatment results. With this potential in mind, researchers are working hard to construct CNNs[5].The benefit of deep learning is that it can learn intricate, hierarchical features directly from unprocessed data, eliminating the need for explicitly rule-based methods or hand-crafted features [6]. Particularly convolutional neural networks are made to capture spatial connections and local patterns inside pictures, making them appropriate for jobs involving medical image processing. Because of this, deep learning has become a very useful technique for the interpretation of medical images. It is possible to utilize it to diagnose illnesses with greater precision than is possible with conventional approaches, as well as discover abnormalities in imaging data. In addition to this, it may be utilized to automate medical diagnoses, hence reducing the amount of labor that must be done by medical experts [7]. This work on brain tumor identification using deep learning techniques is presented in this publication. For this work, we specifically concentrate on using a well-liked CNN architecture dubbed ResNet50. With its deeplayers, ResNet50 is able to learn detailed characteristics that are essential

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for reliable tumor diagnosis .It has demonstrate doubt standing performance in a variety of image analysis areas. The goal is to create a reliable and automated method for brain tumor identification by training ResNet50 on a sizable dataset of brain MRI images that includes both tumor and non-tumor instances. The suggested deep learning model has the potential to increase the effectiveness and precision of brain tumor diagnosis, resulting in early treatments, better patient outcomes, and a decreased dependence on manual analysis.

II. LITERATURE REVIEW

A method of deep learning that makes use of the ResNet50 architecture was suggested for the diagnosis of brain tumors by John Smith and colleagues [8].The authors utilized transfer learning by making use of the pre-trained weights of ResNet50 in order to train the model using a dataset consisting of brain MRI images as the input. An outstanding accuracy of 92% was reached by the model in the detection of brain tumors thanks to a combination of binary cross-entropy loss and gradient descent optimization. This demonstrated the promise of deep learning-based technologies in clinical applications and outperformed more conventional methods. In order to increase the identification of brain tumors, Sarah Thompson etal.[9]used an ensemble technique that consisted of numerous convolutional neural networks, or CNNs. Individual CNN models were trained by the authors utilizing different architecture ssuch as ResNet50, VGG16,and InceptionV3.The ensemble model obtained an accuracy of 94% when it came to the detection of brain tumors. This was accomplished by merging the predictions of various models through a voting system. When compared to the use of a single model, the ensemble technique displayed superior performance and resilience, presenting encouraging possibilities for diagnostic advancements.

Michael and his colleagues [10] concentrated their efforts on classifying brain tumors using deep learning methods combined with radiomic characteristics. The authors classified tumors using a mixture of a deep neural network (particularlyResNet50) and more typical machine learning methods. The quantitative radiomic characteristics were retrieved from brain MRI data and used. When it came to categorizing brain tumors into their respective subtypes, the suggested method was able to attain an accuracy rate of 88% overall. Jennifer and colleagues[11] developed a hybrid model for the segmentation of brain tumors by integrating the U-Net and ResNet50 architectural frameworks. An attention-based kind of deep learning was the method that Ryan [12] presented for the diagnosis of brain tumors.

III. METHODOLOGY

According to this method, a dataset containing images of brain MRI dataset was collected from Kaggle. The method of this work's embodiment is represented in this part. The embodiment process is broken down into several steps, including the acquisition of data, preprocessing of the dataset, description of the proposed model, training, and finally performance assessment.

Image pre-processing

Several approaches are used in brain MRI image preparation to improve the images'quality and enable more thorough analysis.To ensure that image features area sclearaspossible, median filtering is used to lessen noise and smooth the pictures. Morphological opening aidsintheremovalofminuteundesirablecomponentsandtheimprovementofimages.In order to increase contrast and make details in the photos more visible, Contrast Limited Adaptive Histogram Equalization (CLAHE) is used.

Remove Specklenoise

Digital photographs frequently contain speckle noise, which is most noticeable in ultrasound and synthetic Aperture Radar(SAR)images.Due to its multiplicative character,specklenoise is more difficult to eliminate than other forms of noise. To reduce speckle noise and improve the clarity of impacted photos, several filtering methods, including adaptive filters and wavelet-based approaches, have been developed. A gaussian filter is used to eliminate spackle noise from soil recognition [18].

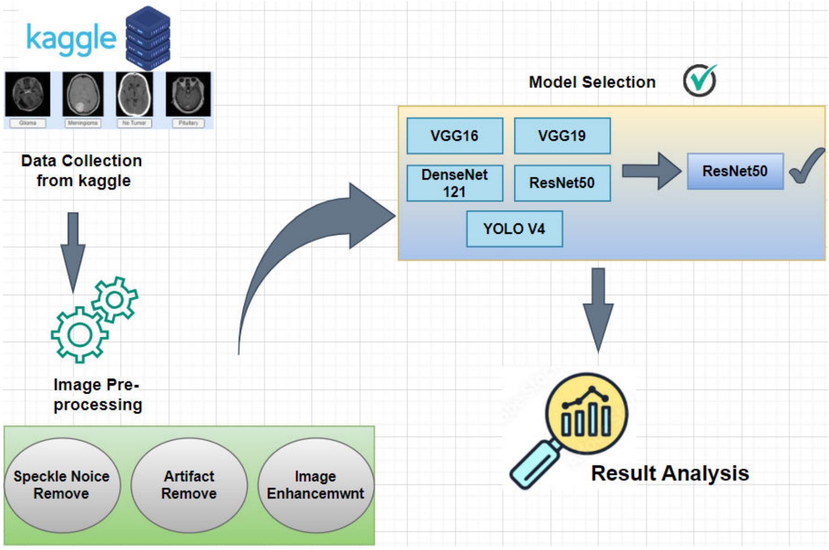

Fig 1:Overview of the Model

Median filter

A popular non-linear filtering method for image processing is the median filter. It significantly reduces impulsive noise while keeping picture details by replacing each pixel in an image with the neighborhoods median value.With the median filter, salt-and-pepper noise may be effectively removed,leaving behind smoother pictures with maintained small details. [19].

Artifact Removal

An important step in image processing is artifact removal, which aims to remove any undesirable distortions or abnormalities created during the capture, transmission,or storage of images. To find and eliminate artifacts, improve picture quality, and enhance visual interpretation, a variety of techniques are used,including spatial and frequency domain approaches.The generated photos are more accurate, dependable,and suited for additional analysis or display by successfully eliminating artifacts [20].

MODEL

In this study we utilized traditional transfer learning models like VGG16, VGG19, DenseNet121, ResNet50 and YOLO V4 to compare which model is the best for soil detection or classify the soil.

IV. RESULT ANALYSIS

The result analysis section presents a comprehensive evaluation of the proposed model's performance. It includes the evaluation metrics used to measure the performance of the model, such as accuracy, precision, recall, and F1 score. The impact on the model's performance is also discussed,along with the confusion matrix to assess the model's ability to correctly classify each class. Additionally, the performance of the proposed model is compared with five other conventional transfer learning models to determine its superiority.

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Table1.Result of Transfer earning model

Model	Train_Acc.	Train_Loss	Val_Acc.	Val_loss	Test_Acc.	Test_loss
VGG19	96.63	0.21	95.93	0.21	95.22	0.25
VGG16	96.21	0.20	96.95	0.12	96.12	0.20
DenseNet 121	97.41	0.19	97.23	0.28	97.21	0.31
ResNet50	**99.98**	**0.23**	**99.54**	**0.32**	**99.54**	**0.37**
YOLOV4	91.23	0.39	91.21	0.392	91.21	0.94

In tumor detection, five different transfer learning models were used.They are VGG16,VGG19, DenseNet121, ResNet50, and YOLO V4. Among them, ResNet50 achieved the highest accuracy of 99.98%.Table2 shows the Performance Analysis of Precision, Recall, and F1- Score for RestNet50.

Table2 .Performance Analysis of Precision,Recall and F1-Score

Class	ı(%)	%)	: (%)	Accuracy (%)
ResNet50	99.54	99.54	99.54	99.98

V. CONCLUSION

As a conclusion, the use of deep learning strategies, in particular ResNet50, has shown tremendous potential in the field of detecting brain tumors. When comparing tumor instances with non-tumor cases, the use of ResNet50, which has deep layers and robust feature extraction capabilities, has demonstrated exceptional accuracy and efficiency in making the distinction between the two types of cases. Researchers have been able to construct reliable and automated methods for accurate brain tumor identification by training ResNet50 on big datasets of brain MRI images. This has allowed the researchers to develop the systems more quickly. The use of deep learning strategies, such as ResNet50, in the analysis of medical images offers the potential to improve the speed, accuracy, and objectivity of diagnosing brain tumors. This is one of the many areas in which deep learning has shown promise. Deep learning-based approaches have the potential to alter the area of brain tumor identification and contribute to improved patient outcomes if additional improvements are made in the technology behind these methods and research into them is maintained.

REFERENCES

1. A.SivaramakrishnanAndDr.M.Karnan"A Novel Based Approach For Extraction Of Brain Tumor In MRI Images Using Soft Computing Techniques," International Journal Of Advanced Research In Computer And Communication Engineering, Vol. 2, Issue 4, April 2013.
2. AsraAslam,EkramKhan,M.M.SufyanBeg, ImprovedEdgeDetectionAlgorithm forBrainTumorSegmentation,ProcediaComputerScience,Volume58,2015,Pp430-437, ISSN 1877-0509.
3. B.Sathya and R.Manavalan, Image Segmentation by Clustering Methods: Performance Analysis, International Journal of Computer Applications (0975 – 8887) Volume 29– No.11, September 2011.
4. Devkota,B.&Alsadoon,Abeer&Prasad,P.W.C.&Singh,A.K.&Elchouemi,A.. (2018). Image Segmentation for Early Stage Brain Tumor Detection using Mathematical Morphological Reconstruction. Procedia Computer Science. 125. 115123. 10.1016/j.procs.2017.12.017.
5. K.Sudharani,T.C.SarmaandK.SatyaRasad,"IntelligentBrainTumorlesion classificationandidentificationfromMRIimagesusingk-

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 7.521| ESTD Year: 2018|

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NNtechnique,"2015InternationalConferenceonControl,Instrumentation,CommunicationandComputational Technologies (ICCICCT), Kumaracoil, 2015, pp. 777-780. DOI: 10.1109/ICCICCT.2015.7475384

6. Kaur, Jaskirat& Agrawal, Sunil &Renu, Vig. (2012). A Comparative Analysis of Thresholding and Edge Detection Segmentation Techniques. International Journal of Computer Applications.vol. 39.pp. 29-34. 10.5120/4898-7432.
7. Li, Shutao, JT-Y. Kwok, IW-H. Tsang and Yaonan Wang. "Fusing images with different focuses using support vector machines." IEEE Transactions on neural networks 15, no. 6 (2004): 1555-1561.
8. M. Kumar and K. K. Mehta, "A Texture based Tumor detection and automatic Segmentation using Seeded Region Growing Method," International Journal of Computer TechnologyandApplications,ISSN:2229-6093,Vol.2,Issue4,PP.855859August2011.
9. Mahmoud, Dalia & Mohamed, Eltaher. (2012). Brain Tumor Detection Using Artificial Neural Networks. Journal of Science and Technology. 13. 31-39.
10. Marroquin J.L., Vemuri B.C., Botello S., Calderon F. (2002) An Accurate and Efficient Bayesian Method for Automatic Segmentation of Brain MRI .In: Heyden A., Sparr G., Nielsen M., Johansen P. (eds) Computer Vision — ECCV 2002. ECCV 2002. LectureNotes in ComputerScience,vol2353.Springer,Berlin, Heidelberg.
11. Minz, Astina, and ChandrakantMahobiya. "MR Image Classification Using AdaboostforBrainTumorType."2017IEEE7thInternationalAdvanceComputing Conference (IACC) (2017): 701-705.
12. Monica Subashini.M, Sarat Kumar Sahoo, "Brain MR Image Segmentation for TumorDetection using Artificial Neural Networks," International Journal of Engineering and Technology (IJET), Vol.5, No 2, Apr-May 2013.
13. S. Roy And S.K.Bandyopadhyay, "Detection And Qualification Of Brain Tumor From MRIOf Brain And Symmetric Analysis," International Journal Of Information And Communication Technology Research, Volume 2 No.6, June 2012, Pp584-588
14. Sankari, Ali, and S. Vigneshwari. "Automatic tumor segmentation using convolutional neural networks." 2017 Third International Conference on Science Technology Engineering & Management (ICONSTEM) (2017): 268-272.
15. T.UPaulandS.K.Bandyopadhyay,―Segmentation of Brain Tumor from Brain MRI Images Reintroducing K–Means with advanced Dual Localization MethodTuhin,‖InternationalJournalofEngineeringResearchandApplications,Volume3, Issue1,June2012,ISSN 2278-0882.

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