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Brain Tumor Segmentation And Classification Using U-Net & Efficient Net B5

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Abstract:-Brain tumors represents a significant medical concern andtheirearly and accurate detection plays very importantrolein improving treatment outcomes. Among the available diagnostic techniques,Magnetic resonance Imaging (MRI) is the most common method used to detect braintumors , but analyzing MRIs cans manually takes a lot of time and depends heavily on expert doctors. This manual process may raise the errors and delay in the process. This study proposes an automated framework for brain tumor detection using Deep learning models which is useful in detection of tumor cells and uneven cells using the proposed system combines two models U-Net and Efficient NetB5 . Where U-Net is used for segmentation that includes highlights the exact tumor location in MRI image by separating it from Healthy brain tissue. After segmentation the identified cancer region under goes to Efficient netB5,which is a deep learning model designed for classification. Efficient NetB5 classifies the tumor belongs to which type such as Glioma, Meningioma or Pituitary tumor. The proposed combination model is not only able to detect where tumor is located but also identify what type of tumor it is . Tests on standard MRI datasets show that this approach improves accuracy , reduce errors and speed up the treatment process. Our project is a additional scope for professionals to analysis the patient condition and provides a reliable computer based tool for faster and better treatment planning

Keywords:- Efficient-Net; U-net; Accuracy; Glioma; Meningioma; Pituitary; Segmentation; Classification Union; Neuro-Diagnostic; Magnetic resonance Imaging(MRI)

Introduction

Brain tumorsare most serious life threating conditions and can significantly affect survival rate of a person. They are caused due to abnormal cell growth within the brain cells or central nervous system. Also non-cancerous or benign tumors can cause complications by compressing surrounding tissues and disrupting normal functioning of brain. For this reason, early identification and correct classification are important for selecting suitable treatment techniques and improving patient health. Predicting stage of tumor by manual analysis is may delay the diagnosis. The need of fast and accurate identification of cancer cells is required to avoid the mortality rate.

MRI is most commonly used for brain tumor diagnosis due to the availability of detailed visualization. MRI scans are helps to identify the tumor size, shape, its position over several image slices .
The manual analysis is very time consuming and requires expertise.

In the proposed model the combination of Efficient netB5 and U-Net used for segmentation and classification for making the accurate analysis. Efficient NetB5 is used in this work due to balanced scaling network width, depth, size ect, and U-Net specifies the type of the tumor .

2.LITERATURE SURVEY

Brain tumor is one of the dangerous and stages wise disease. That can be identifiable in early stages using MRIand other medical imaging models. Mostly and highly used to detect the tumor cells is MRI for the several image slices. Manual analysis may overatted due to the errors in segmentationand classification of brain tumor. This made the high requirement of automated brain tumour detection systems using machine learning methodologies.
This section contains the previously proposed models and from where the forestep of our proposal taken and why we chosed our models
A model proposed by Mohamed Salh in 2024, comparison between ResNet and Efficient Net for Image Classification resulted the both models ResNet and Efficient Net have there own abilities for classification but Efficient Net has high accuracy rate compaired with the Resnet . Efficient Net due its compound scaling stratergy , achieves a good balance between accuracy and efficiency[1]

Hybrid Model using CNN with ResNet and Unet models developed in 2023, concluded that “brain tumor classification and detection in MRI images the results indicate that the fine-tuned ResNet model”[2] more accurate then the CNN model that provides Accuracy of 0.94 for non tumor and 0.96 for tumor

The importance of Deep learning models in brain tumor detection plays a huge role to maintain the high accuracy and scalability. The study by Reddi Prasadu in 2024 addresses the emergency need for identification of improper cell in brain for early stage of tumor detection. In “the proposed model Improved Binomial Thresholding-Based segmentation (IBTBS) for efficient segmentation”[3]

Hybrid frameworks proposed to combine types of classification and segmentation models. The authors concluded that a hybrid model is provides a better resultsthen a single or individual model[4]

Additionally a study conducted by Dr.J.K.Periasamy in 2023 that mentioned the comparison between the VGG -19 and ResNet -50 obtained the result that ResNet-50 performs outstanding while compared with the VGG-19.It results the accuracy of 0.97 where VGG-19 provides 0.96[5]

“On the basis of analysis conducted, VGG-19 and ResNet-50 have high performance in Brain tumor detection.
ResNet-50 is found to have higher precision and accuracy” [6]0.9795 and 0.9791

A optimized deep learning approaches combined with advanced segmentation techniques further improvement detection efficiency[7]
An improved Binomial Thresholding Based Segmentation is introduced for efficient segmentation”[8] bring the brain tumor detection easier

3. METHODOLOGY

3.1 System Architecture Overview

The paper explains the method and architecture of the proposal. This tries to present a Efficient net coupled with U-Net. Further subsections describe how the model functions and the methodology adopted for the segmentation and classification of brain tumors.A modular architecture organized into four functional subsystems: data preprocessing, segmentation ,classification ,and visualization interface. These subsystems operate sequentially within a internal pipeline, coordinated by a central logic controller that manages data flow and resource. The proposed brain tumor detection system is designed as a modular deep learning pipeline that performs both cancersegmentation and tumor type classification using Magnetic Resonance Imaging (MRI) scans. This study approaches advanced CNN architectures to achieve high accuracy. The overall methodology is divided into multiple functional modules, each responsible for a specific task in the diagnosis process.

The process starts with loading the MRI image and preparing it for analysis. The segmentation system then converts the image into grayscale and identifies the tumor area by creating a binary mask .At the same time the classification system unders goes for examination on the RGB image to estimate the probability of different pathological conditions. Finally the result from both systems are combined and displayed on the results section for user visualization. The whole architecture is initially works under two different phase but finally provides a single r

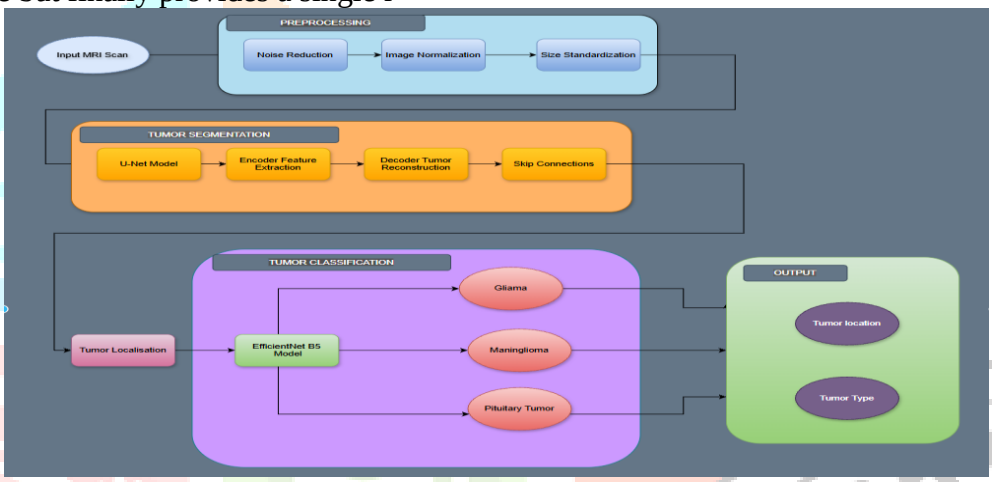


Figure 1 : Architecture of proposed model

3.2 Segmentation Subsystem

Segmentation is done by using U-Net model where it is highly suitable.

- **Encoder-Decoder Structure:** We used a U-Net with an encoder that is pre-trained on image net.This helps the model use strong feature representations.The decoder rebuild a detailed binary mask of size 256*256 pixel
- **Dice Loss Formulation :**The tumor area usally occurs in small regions in the image,This is leads to class imbalance problem.the Dice Loss function ,which focuses detect the overlap between the predicted and actual tumor regions

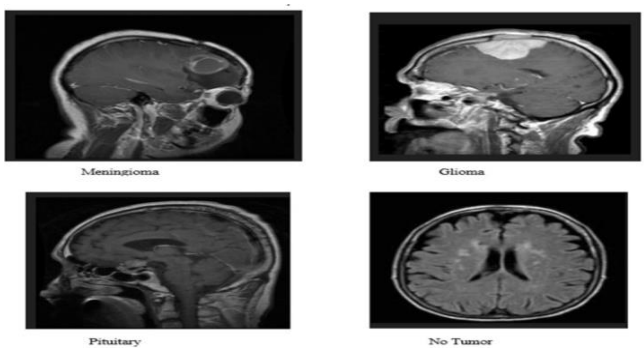
$$L_{\{Dice\}} = 1 - \frac{2\sum \hat{y}_i \{y\}_i}{\sum y_i + \sum \{y\}_i}$$

3.3. Classification Subsystem

The classification subsystem using Efficient netB5 to identify the correct type of brain tumor.This model used due to high accuracy noted in various studies

- **Fine-Tuning Strategy:** The system uses transfer learning , starting with pre-trained on the imagenet dataset. The starting layers which perform general featuresare kept frozen.Mainly the two layers are convolutional blocks and a custom classification layer are fine-tuned.

- **Class Balancing:**class balancing is used to handle the imbalance between different tumor classes,A weighted cross entropy loss function was adopted so that underrepresented classes could contribute more effectively to the learning process. In final stage , a softmax activation function is used on the output layer to produce probability scores for each category



.**Fig 2**: *Sample MRI slices representing the four diagnostic classes*

3.3 Evaluation Metrics

The Evaluation Metrics defines that the operation take placed during the model implementation

Segmentation Metrics (U-net): Due to healthy tissues background pixels the accuracy is misleading, To rectify this we used Overlap-based metrics

Dice Coefficient: It tells how similar the predicted segmentation is to real tumor area.

$$\mathbf{DSC} = \frac{\mathbf{2} \times |\mathbf{X} \cap \mathbf{Y}|}{|\mathbf{X}| + |\mathbf{Y}|}$$

Intersection over Union (IoU): how much predicted tumor area overlaps with the real tumor area $\mathbf{IoU} = \frac{|\mathbf{X} \cap \mathbf{Y}|}{|\mathbf{X} \cup \mathbf{Y}|}$

3.4 **Classification Metrics(EfficientNet):**To validate the implementation of a classification model

Accuracy: The ratio of correct prediction so total predictions

$$\mathbf{Accuracy} = \frac{\mathbf{TP} + \mathbf{TN}}{\mathbf{TP} + \mathbf{TN} + \mathbf{FP} + \mathbf{FN}}$$

Precision &Recall :majority of true value predicted and ability to find all actual positives.

$$\mathbf{Precision} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FP}}, \boldsymbol{Recall} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FN}}$$

F1 score : The balance between precision and recall is plotted by F1 Score

$$\mathbf{F1} = \mathbf{2} \times \frac{\mathbf{Precision} \times \mathbf{Recall}}{\mathbf{Precision} + \mathbf{Recall}}$$

Table.1 performance summary vs target

MODEL COMPONENT	METRIC	TARGET	ACHIEVED
U-NET SEGMENTATION	Dice Coefficient	>0.70	>0.80
	IoU Score	*>0.60*	*>0.70*
EFFICIENT-NET CLASSIFICATION	Glioma Accuracy	*>80%*	*95.4%*
	Meningioma Accuracy	*>75%*	*93.5%*
	Pituitary Accuracy	*>90%*	*98.0%*
	No tumor Accuracy	*>95%*	*98.48%*
	Overall Accuracy	*>85%*	*96.36%*

Fig 3: *The user interface and diagnosis results*

4. EXPERIMENTAL RESULTS

The Proposed models Efficient Net and U-Net works powerfully and provides high accuracy in segmentation and classification

Classification Training (Efficient Net-B5) : The model perfoms a vast convergence, with high accuracy rate of 0.98.The techniques are successfully mitigated

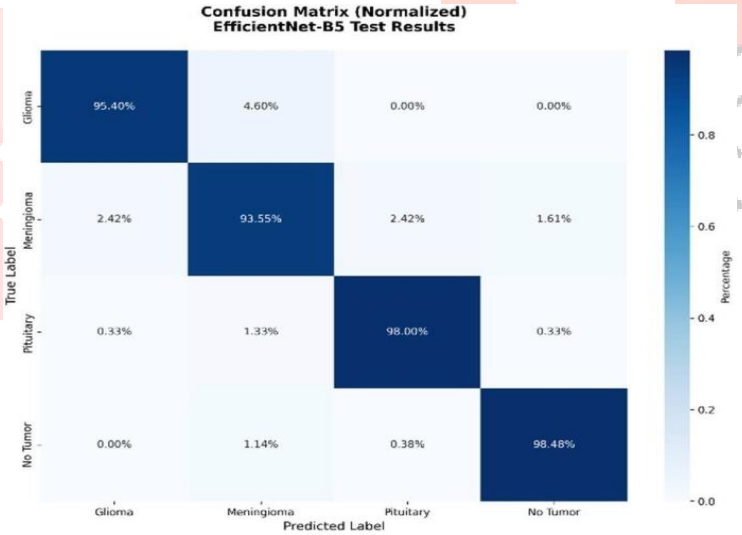
Segmentation Training (U-Net):

The U-Net shows a clear improvement in the results as shown in the fig. That recorded DSC from 0.2 to 0.88and IoU near 0.8

Fig.3.U-NettrainingmetricsincludingDiceLoss,IoU Score, and Dice Coefficient.The model achieves astableIoU> 0.75, validating its ability to precisely localize tumor regions.

Confusion Matrix: It shows thecomparing the actual values with predicted values

- **Minor Confusions:** The primary source of error was as light confusion between



5. CONCLUSION

The study on Efficient NetB5 , U-Net to classification and segmentation of brain tumor using MRI images. U-Net is used for segmentation where Efficient Net is used for classification .The performance measures as it has Precision 98%, Recall 97% , F1 score 97% and accuracy 94% .From the segmentation of this model “IOU is 0.95, DSC is 0.95, and SI is 0.95”.These results confirm that the proposed model is very effective for the segmentation and classification of brain tumors with high accuracy, making it an important tool for enhancing clinical diagnosis and treatment conclusion

Reference	Models Used	Data Set	Result
[7]	Multi-level Threshold technique	BRATS 2015	Accuracy 0.89
[6]	Optimization Morphological technique	BRATS 2015	Accuracy 0.90
Compared model	Resnet with U-net	BRATS 2020	Accuracy 0.95
Our model	Efficient Net B5 With U net	BRATS 2020	Accuracy 0.98

Table 2. The following values are statistical values of the Related models

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