International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 24s, 2025
https://theaspd.com/index.php

Automated Brain Tumor Classification from MRI using a pretrained ResNet50 architecture

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Abstract— *In today's era, accurately and promptly detecting brain tumors is important for effective patient care. Although MRI is a popular technique for examining a patient's brain structure and detecting medical abnormalities, manual interpretation can be time-consuming and may vary depending on the individual. This research employed a fine-tuned ResNet-50 pre-trained architecture, which has been pre-trained on the high-volume ImageNet dataset, for the automated classification of four types of tumor images using a recently popular transfer learning technique.*
The suggested approach employed 3264 MR images, divided into training and testing data. After analysis of training and testing data, the model achieved 51% accuracy on test data. Furthermore, the outcome highlights the task's complexity and suggests possibilities for improvement in future work. The research work highlights the promise of transfer learning but suggests further optimization, including the application of advanced techniques and a comparative analysis with other pre-trained architectures, to enhance diagnostic accuracy. In addition, future work suggests advanced fine-tuning strategies, regularization techniques, and other methods to enhance model performance, thereby aiding medical professionals in brain tumor diagnosis.
Keywords– *Brain tumor classification, Deep learning, Transfer learning, ResNet50 architecture.*

I. INTRODUCTION

A brain tumor is a special kind of tissue growth that is formed by unwanted cells in the human brain [1]. Mainly, it is defined using two classes, primary and secondary. The tumors that belong to the primary class generally develop in the brain and do not affect other human organs. While the secondary brain tumors do not develop in the brain parts but they spread from other body parts. There are further common types of tumors, malignant and benign [2]. Malignant is a high-grade or cancerous type of tumor, while benign is a low-grade or non-cancerous type of tumor [3]. Among all the medical imaging techniques, MRI is the most common and popular method utilized in investigating brain images [4]. The tumor identification in the early stage of its formation is very important in the inpatient treatment process. The medical professionals generally use image classification techniques to further differentiate the MR images.

Image classification tasks by traditional and manual methods are laborious and expensive. Additionally, they can get conflicting results from different investigators. Therefore, to overcome these conflicts, an automatic image classification method is needed [5].

The recently developed technique of deep learning plays a significant role in the medical field in investigating brain tumors [6].

To improve classification performance and resolve data set training issues transfer learning technique can be used [7]. It is an advanced deep learning-based method in which previously trained attributes on a large dataset can be directly applied to a smaller dataset. Among the various advantages of transfer learning, the main ones are to reduce training time and computational resources [8].

Due to the advancement of technology, there is a potential for significant improvement in the performance of tumor classification by utilizing the power of pre-trained models [9]. The objective of this research is to examine and highlight the effectiveness of the popular ResNet50 framework using transfer learning to improve the performance of MRI classification, under conditions with a small training dataset [10].

In the rest of the paper, the next section explains the existing related studies and Section III highlights the material and methods with the methodology. Section IV discussed results and experiments, and the last section concluded the paper.

II. RELATED WORK

In recent years, for the medical image classification task, various techniques have been suggested. Sultan et al. [11] suggested a deep neural network architecture based on CNN to classify tumors into different types and grades. The suggested framework achieved excellent performance with 96.13% and 98.7% accuracy on two datasets. It highlights the importance of deep neural networks in classifying MR images. In paper [12], Alqudah et al. discuss tumor classification using CNN to grade tumors into three classes. It utilizes 3064 brain images, achieving high accuracy rates of 98.93%, 99% and 97.62% on different categories of images. The research defines the importance of deep learning techniques in the tumor classification process.

The paper Badža & Barjaktarović [13] discusses the segmentation of tumors using CNN. This CNN architecture was specifically designed for the segmentation of brain tumors. The study demonstrated a high accuracy of 96.56% using a record-wise cross-validation method on an augmented dataset, highlighting the potential of CNNs as effective decision-support tools for radiologists in non-invasive tumor diagnostics.

Jena et al. [14] employ various supervised machine learning algorithms for classification tasks. After experimenting, it reported an accuracy of 94.25% with SVM. 87.88% with KNN and 89.57% with Binary Decision Trees (BDT). These methods utilize texture features generated from different weighted MRIs (FLAIR, T1C, and T2) to classify brain tumors effectively.

Bahuguna et al. [15] focus on utilizing deep learning. It employs a dataset of 3064 brain scans. The study enhances the dataset by including axial images of healthy brains, thereby improving the neural network's performance in accurately classifying brain tumors.

Anusha & Reddy [16] discuss tumor classification by employing a VGG-19 pre-trained model. It classifies four types of tumor classes. The study utilizes 7022 MRI scans and combines outputs from multiple classifiers through a weighted average ensemble method, achieving 98.87% accuracy, with individual class accuracies reaching up to 99.78% for Glioma.

The research paper Anitha et al. [17] presents a comparative study based on various classifiers using Magnetic Resonance (MR) images. It employs various categories of classifiers. The study finds that a hybrid classifier produces 98.8% accuracy. Sarkar et al. [18] present an AlexNet pre-trained model for feature extraction. It employs various categories of classifiers, such as BayesNet, SMO, etc. It achieved excellent accuracy for the respective classifiers.

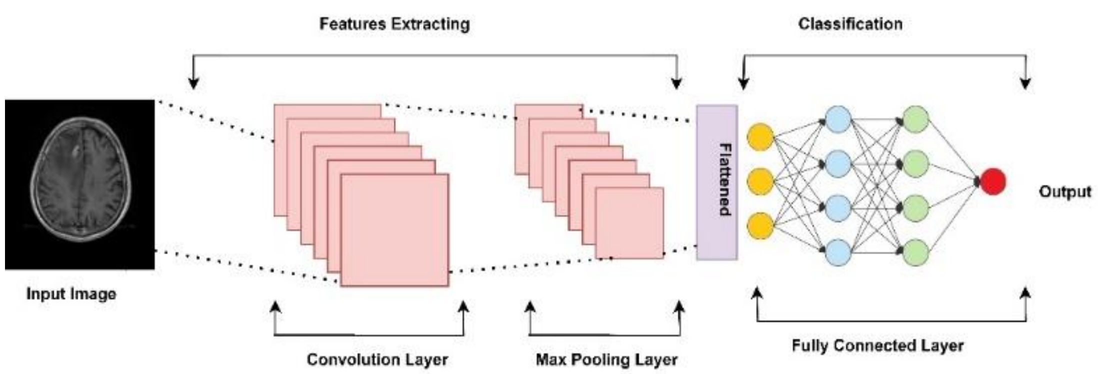
Kollem et al. [19] present a deep learning model. It divided tumors into different categories. By employing transfer learning and EfficientNet, the proposed approach outperforms conventional deep learning techniques in accuracy. This method leverages publicly accessible datasets, making it a significant advancement in the area of tumor classification, which is crucial for determining appropriate treatment strategies.

Rao & Reddy [20] present a hybrid classifier approach. It emphasizes the advantages of ML, basically in training on small datasets and lower computational complexity. The hybrid classifier combines SVM, DT, and KNN classification algorithms.

Based on the above literature review, it is clear that deep learning using CNN is a very important technique in the automated tumor classification area. Furthermore, the applications of recently developed advanced techniques, like transfer learning in medical imaging, are still an active and popular area of research.

III. METHODS AND MATERIALS

The following section describes important components related to the practical implementation of the suggested framework.



A. Convolutional Neural Network(CNN)

CNN is a popular and advanced DL based architecture that extracts significant features from medical images, analyzes those attributes, and accurately classifies them [21].

A basic CNN architecture contains some important layers in its basic structure, like convolutional, max-pooling, and fully connected (Figure 2). A CNN applies a distinct set of filters to each layer. A CNN automatically picks up these filter values throughout the training phase.

1) Kernel: A small matrix that moves across a large image from top to bottom and left to right might be considered a kernel. All of the input image's pixels are convolved with the kernel at that pixel's neighbourhood, and the result is saved. CNNs can learn kernels that are capable of identifying edges and structures in lower-layer network architectures. These filters may then utilize the borders and frameworks as " constructing elements" to identify higher-level objects in the network's denser layer.

Convolution filters, pooling, back propagation, and nonlinear activation functions are used to achieve this.

2) The convolution layer: A CNN's components, which are called the convolution layer, are considered its fundamental components. The parameters of the convolution layer contain a set of filters, which is also called a kernel. Figure 1 below represents the forward pass of the CNN [22].

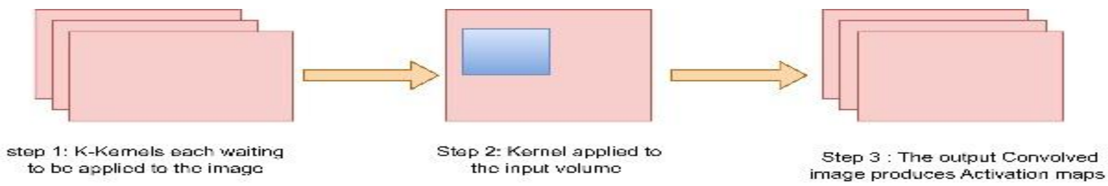


Fig. 1. Convolution operation of k-filters on the image

3) Activation: A nonlinear activation function has been implemented after the convolution layer.

An activation layer applies the activation function after receiving input data. The resultant data of an activation layer is generally equal to the input data [23].

4) Pooling layers: In CNN, there is a need to decrease the quantity of source input. For this purpose, we can use Pooling layers.

According to the CNN framework, the primary role of these layers is to minimize the size of the input images. By doing this, we can minimize the computation time and working parameters. Control overfitting is another benefit of pooling. In the Max pooling layer, we have employed the max function[24].

5) Flatten layer: This layer is used to flatten a 3-dimensional matrix into a 1-dimensional matrix [25].

6) Dense layer or fully connected layer: A unit of output is dense. It classifies the features into various categories using the SoftMax activation function.

Fig. 2. Architecture of a convolutional neural network

B. Transfer Learning

Transfer learning (Figure 3) is a recently developed advanced technique for applying previously acquired knowledge from one task to another task for the purpose of feature extraction and classification. In our proposed brain tumor classification framework, we applied this technique to train our ResNet50 pretrained model. Using transfer learning on a pretrained model, computation time is reduced and performance is improved [26].

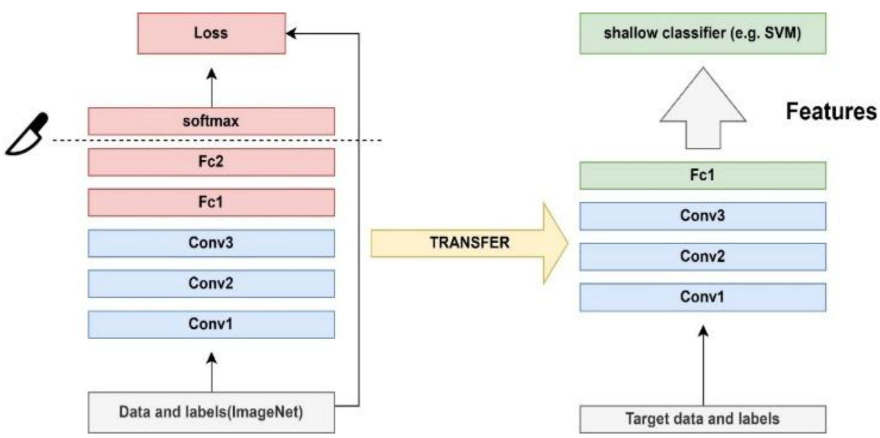


Fig. 3. Transfer learning technique

C. ResNet50 Pre-trained Architecture

ResNet50 (Figure 4) is a famous framework known as the Residual Network, which comprises 48 convolutional layers, one MaxPooling layer, and one average pooling layer [27]. Total, it consists of 50 CNN layers. Due to the large number of layers, this type of model may not achieve high accuracy. So this architecture comes with the idea of skip connections that connect the result of the previous layer directly to the stack layer. This idea can resolve the popular problem of vanishing and exploding gradients. The original ResNet34 model contains 34 layers, which were further upgraded to 50 in the ResNet50 architecture by changing the existing two-layer block with a three-layer bottleneck block. The upgraded block reduces the parameters and simplifies the matrix multiplication process by applying 1×1 convolutions, which converts the model into a more accurate form, making it faster than other similar kinds of pretrained models. We can represent the residual block equation in the following way:

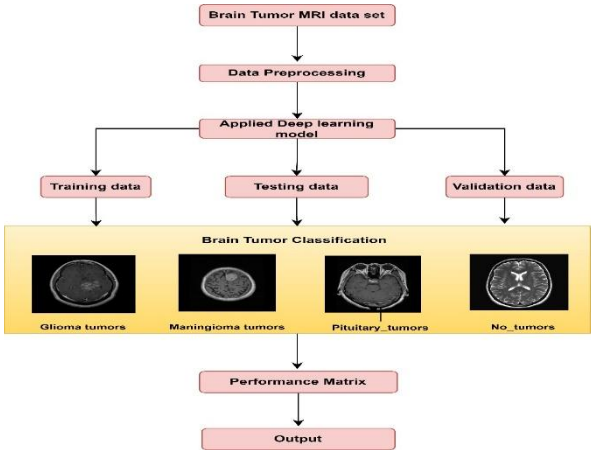
$$Y = F(X, \{W_i\}) + X \qquad \text{------} \ (1)$$

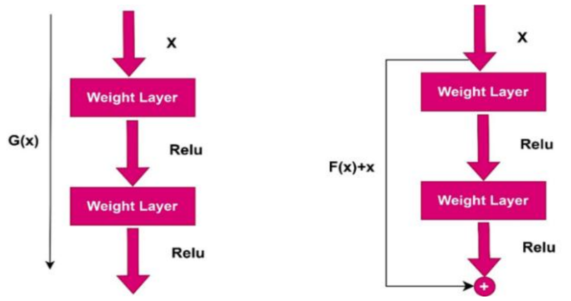
Where :

- $F(X, \{W_i\})$ is the framework residual mapping
- X Is the input
- Y Is the output
- If dimensions differ, we use a projection:

$$Y = F(X, \{W_i\}) + W_s X$$

W_s It is a linear transformation (1x1 convolution) to match dimensions.





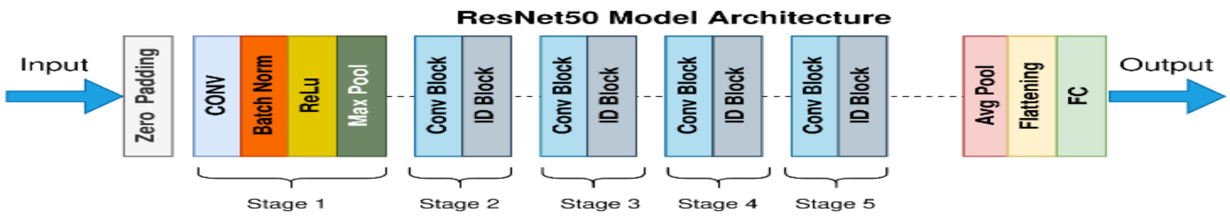


Fig. 4. The ResNet-50 Pretrained Model Architecture

In our proposed research work, we employed this architecture with an image input size of 128 X 128.

D. Proposed Methodology

In our proposed experimental activity, the input data is downloaded from the online data repository website Kaggle. It contains 3264 MR images, which are further split into two categories of input data: training 2870 images and testing 394 images [28]. Our suggested experiment is performed by providing a training process to the ResNet50 model. During the experimental process, the MRI classification follows some essential steps, which are categorised into three popular steps like preprocessing, feature extraction, and classification[29]. The following figure 5 represents our proposed workflow.

Fig. 5. Brain Tumor Classification Flow Graph

According to the workflow, the pre-processing step downsized the images. In our experiment, the image size was 128 X 128. The pre-trained model required a high volume of data for the training process. Generally, the use of a small amount of data generates an overfitting problem, which may be avoided or decreased by using a data augmentation technique to produce a high volume of image data. The transfer learning technique is used for obtaining the attributes from the proposed architecture. Generally, low-level attributes and high-level attributes are extracted from initial layers and inner layers[30]. The various parameters of the proposed ResNet50 model are shown in Figure 6.

Layer (type)	Output Shape	Param #
resnet50 (Functional)	(None, 4, 4, 2048)	23,587,712
flatten_3 (Flatten)	(None, 32768)	0
dropout_6 (Dropout)	(None, 32768)	0
dense_6 (Dense)	(None, 128)	4,194,432
dropout_7 (Dropout)	(None, 128)	0
dense_7 (Dense)	(None, 4)	516

Total params: 27,782,660 (105.98 MB)
Trainable params: 5,249,668 (20.03 MB)
Non-trainable params: 22,532,992 (85.96 MB)

Fig. 6. Proposed ResNet50 framework parameters

The experiments were performed on the Google Colab environment using Python [31]. The default Google Colab GPU session with RAM and a hard disk is utilized for standard computing. The TensorFlow framework and Keras library were used for coding purposes.

The suggested framework consists of the following steps:

- Acquired brain tumor image categories for training and testing.
- The input MR images are resized into 128X128, and to increase input data volume, a data augmentation method is applied.
- Using a pre-trained ResNet50 framework, various features are extracted.
- At last, the softmax activation function performed the classifier role.
- The confusion matrix shows the test labels and predicted labels.
- The various performance parameters measured model accuracy.

E. Model Evaluation Metrics:

Evaluating a framework's efficiency is crucial to determining its effectiveness and reliability. Therefore, our proposed research work uses the following evaluation matrices to evaluate the suggested framework [32].

1) Accuracy: It determines the correct prediction percentage against the total test data. The following equation presents the formula.

$$\text{Accuracy} = \frac{(\text{TP+TN})}{(\text{TP+FP+FN+TN})} \qquad (1)$$

2) Precision: It determines the correct class compared to the positive predictions generated. Precision is presented by the equation below.

$$\text{Precision} = \frac{\text{TP}}{(\text{TP+FP})} \qquad (2)$$

3) Recall: Determining all positive values of the targeted class is called recall. The following formula represents recall.

$$\text{Recall} = \frac{\text{TP}}{(\text{TP+FN})} \qquad (3)$$

4) F1-score: It does not determine using the simple average; instead, it uses the harmonic average of precision and recall to distinguish itself.

$$\text{F1} - \text{score} = \frac{\textbf{(2xPrecisionxRecall)}}{\textbf{(Precision+Recall)}} \qquad (4)$$

In the above equations, TN, TP, FN, and FP are the commonly used abbreviations that represent various classification values.

5) AUC-ROC: The ROC curve plots the recall value against the 1-specificity for different threshold values. The AUC score 1 indicates the 100% accuracy of the framework, and score 0 represents the 0% accuracy of the proposed framework[33].

IV. Results and Discussion

A. Training and Validation Performance

According to the results, the classification algorithm performed well in classifying various brain tumors using MR images. According to the output, the accuracy on training and test data was 64.11% and 50.76%. The robust and consistent output of the ResNet50 framework suggests its significance in accurate tumor diagnosis. The accuracy and loss performance are visualized using Figures 7 and 8.

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 24s, 2025
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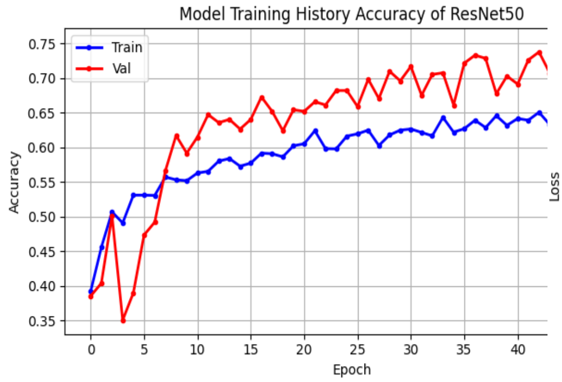
The generated accuracy and loss graph indicate variations in the model's performance [34].

Fig. 7. Training & Validation Accuracy Graph



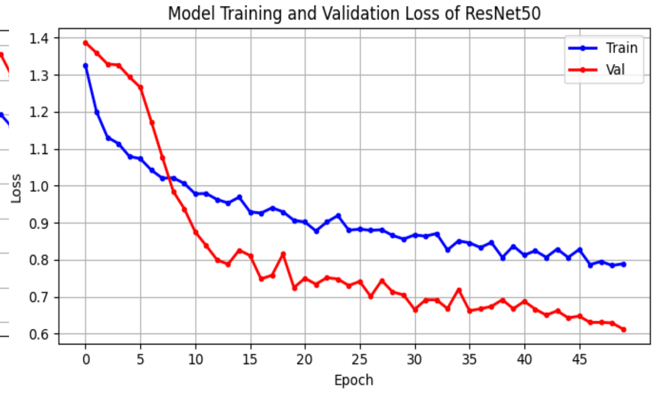
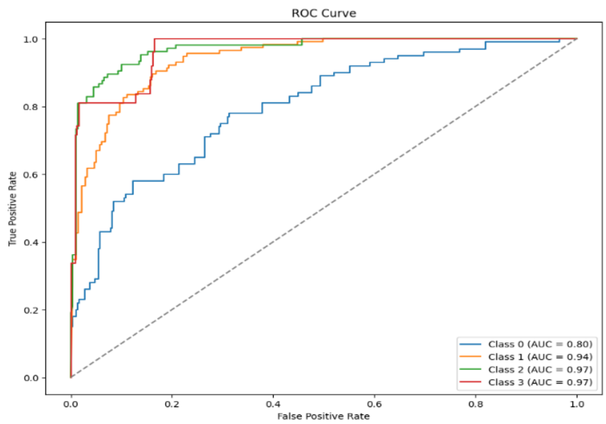


Fig. 8. Training & Validation Loss Graph

B. Confusion Matrix

The following diagram (Figure 9) represents the popular confusion matrix for the ResNet50 architecture [35]. This confusion matrix shows the actual counts of positive and negative parameters for each tumor class. It provides a detailed performance overview, highlighting misclassifications and helping to understand the strengths and weaknesses of each tumor class..



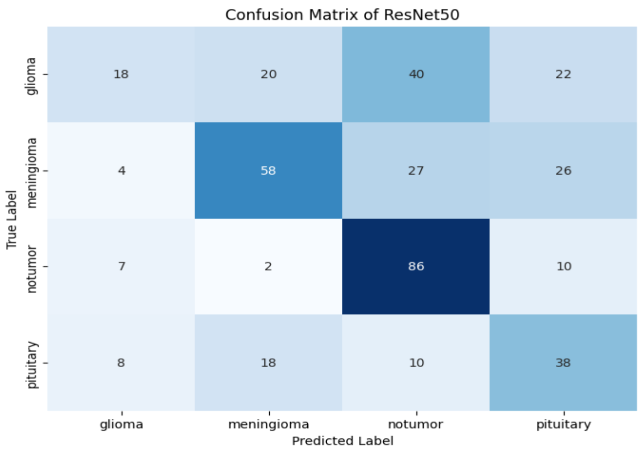


Fig. 9. Confusion Matrix of Test Data Set

C. Classification Report

The classification report and charts (Figures 10 and 11) present key performance metrics for each tumor class, along with the overall accuracy, as well as the macro and weighted averages across all tumor classes [36].

	precision	recall	f1-score	support
0	0.43	0.19	0.26	100
1	0.60	0.52	0.56	115
2	0.50	0.76	0.61	105
3	0.44	0.54	0.48	74
accuracy			0.51	394
macro avg	0.49	0.50	0.48	394
weighted avg	0.50	0.51	0.48	394

Fig. 10. Classification Report of Various Tumor Classes

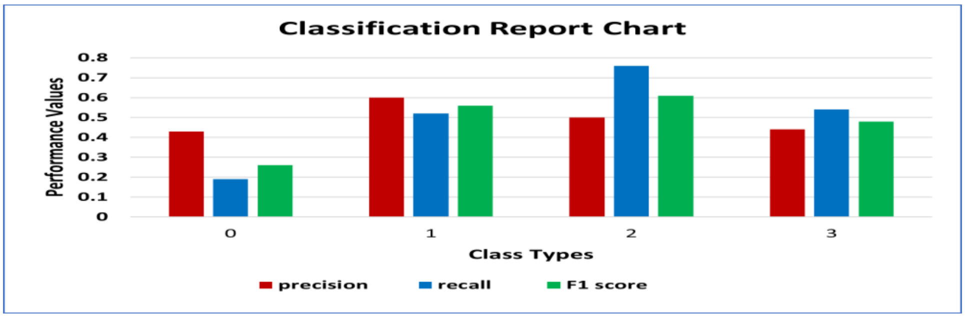


Fig. 11. Classification Report Chart of Tumor Classes

D. AUC-ROC Curve

Figure 12 presents the popular ROC curve and reports the AUC for each tumor class. It evaluates the model's reliability to differentiate all tumor classes. The curve highlights several advantages, such as assessing discriminative power, robustness to class imbalance, and visualizing the relation between TPR and FPR of various tumor classes.

Fig. 12. AUC-ROC Curve among Various Tumor Classes

V. CONCLUSION AND FUTURE SCOPE

The performed research analysed the use of the famous ResNet50 architecture, which has been pretrained on a large volume of the ImageNet dataset. It applies a transfer learning technique to classify MR images into four different categories.

The model was fine-tuned [37], and the acquired images were categorized into three groups to assess generalization performance. Experimental accuracy indicates the proposed framework's ability to work significantly better than arbitrary chance and the potential for further performance enhancements.

Additionally, the popular ROC-AUC curve defines the proposed model's discriminative ability to explain the efficiency of each tumor class against the rest. The ResNet50 model's training process, visualized by the graphs. The model's training accuracy increases and training loss decreases over epochs. In brief, as we have observed, the fine-tuned ResNet50 model provides a foundational baseline for a brain tumor MRI classification method on this dataset. The experimental model's outcome indicates the potential of transfer learning in this area, but also emphasizes the necessity of further enhancement.

In upcoming experimental work, our focus will be on reducing the overfitting problem [38], exploring alternative fine-tuning approaches, and potentially investigating more advanced data augmentation methods to improve generalization and achieve higher brain tumor MRI classification accuracy across all experimental tumor classes.

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