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Leveraging ResNet50 and Xception for Accurate Brain Tumor Classification in MRI Scans

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Abstract—For improved treatment and increased chances of survival, brain tumors should be detected early and accurately. Comparing the two most popular convolutional neural networks for automated brain tumor identification from MRI brain scan images: ResNet50 and Xception. A variety of tumor forms under various scanning circumstances were included in the publicly accessible MRI data. Both models were adjusted to the requirements of the medical imaging environment using transfer learning techniques. Accuracy, precision, recall, F1-score, and AUC-ROC score were used to assess the test findings.The studies' findings indicate that both models performed exceptionally well in classification, with ResNet50 exhibiting stronger convergence and stability against overfitting and Xception registering somewhat higher generalization over complicated tumor presentations. By analyzing each model's advantages and disadvantages, the study shed light on how deep learning systems may be incorporated into radiological diagnostics.

IndexTerms—ResNet50,Xception,Deep Learning,Magnetic Resonance Imaging (MRI),Medical Image Classification

I. Introduction

Brain cancers are also one of the most lethal types of cancer, and it carries a high risk of death if not early identified and treated. Because it has improved capability to demonstrate contrast and fine detail in visualising such soft tissues it is, therefore, crucial in diagnosing and tracking brain tumours non invasively. However, manual interpretation of MRI scans can be labour intensive, produce inconsistent results and, requires high level of radiologist skill. This has had the effect of increasing interest in using deep learning methods to automate diagnostic procedures and increase accuracy and consistency in diagnosis.The application of Convolutional Neural Network (CNN) in medical image analysis is dominating, due to the ability of CNNs to learn increasingly complex representations di-rectly from raw data. The vanishing gradient problem in deep networks is addressed by the ResNet50: skip connections are introduced, that support the training of very deep architectures.

The paper measures how successful are ResNet50 and Incep-tion V3 models at analyzing MRI images to classify brain tumors. The architectures are tuned using transfer learning methodologies on a dataset of validated well-annotated MRI scans. This research attempts identifying the effectiveness of both models in tumor detection and tumor type discrimination, measured in accuracy, precision, recall and AUC. A compari-son of such architectures opens the way for improving reliable AI-driven diagnostic tools for neuro-oncology and improved clinical decisions support.

II. Literature Survey

1. In 2016, Pereira et al. suggested employing convo-lutional neural networks (cnns) as a deep learning approach to address the challenge of brain tumor segmentation. Their model incorporated magnetic resonance imaging (mri) images and was specifically designed to accurately identify tumor regions. They created a method that could automatically learn hierarchical features from raw input, resulting in a substantial enhancement in performance compared to conventional ma-chine learning techniques. This study formed the foundation for incorporating deep connections in medical imaging.

2. In 2021, Hemanth and anitha et al. conducted research on deep learning models that utilized resnet50 and xception, aiming to classify brain tumors based on magnetic resonance imaging (MRI) scans. They trained and evaluated their models using a publicly available dataset and found that both networks achieved satisfactory results, with xception outperforming slightly. Based on their research, pre-trained models that have been trained on a large dataset could be used to speed up the training process and improve the accuracy of medical diagnosis.

3. In 2019, Sajjad et al. created a comprehensive classification system for brain tumors using deep neural networks. They integrated a comprehensive network with data augmentation to its maximum potential in handling limited medical data.

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Their method differentiated glioma, meningioma, and pituitary tumors successfully. The study emphasized the importance of preprocessing and data augmentation in improving the generalization capability of deep learning models.

4. In 2019, Afshar et al. have developed a groundbreaking deep learning method using capsule networks for the classifi-cation of brain tumors. Unlike traditional CNNs, the capsule networks ensured that spatial hierarchies were preserved in the data, leading to improved classification accuracy. Despite not using resnet and xception, their contribution played a significant role in illuminating other deep architectures, while also serving as a source of inspiration for future enhancements in tumor recognition tasks.

III. Materials and Methods

A. Dataset descriptions

The dataset utilized in this course comprises MRI images of brain scans that have been divided into **four distinct categories. Glioma, meningioma, pituitary tumor and no tumor.** The division of images within these classes is illus-trated on figure x (your bar chart). Among the different types of tumors, the category with the most images is pituitary tumor, followed by meningioma, glioma, and then other tumor types. This distribution has a moderate class imbalance, which must be taken into account when creating and evaluating training plans. The data represent a genuine clinical sce-nario where non-pathological cases cannot be disregarded, and a comprehensive framework for developing and validating machine learning models for classifying brain tumors into multiple categories has been established.

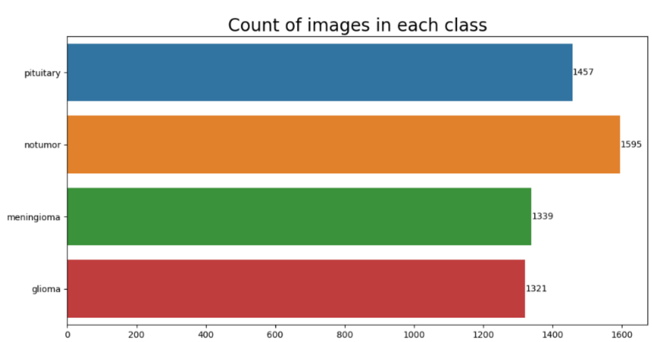

Fig. 1. Distribution of MRI images across four classes: glioma, meningioma, pituitary tumor, and no tumor.

B. Data Preprocessing and Augmentation

The dataset is prepared for both model differently so we can obtain their full potential. Separation of dataset for train ,test and validation take as standard ratio i.e. 80% ,10% and 10%.

Category	count of Images
Train	5712
Test	263
validation	1048

1. Xception: The brain MRI scans were resized to a resolution of 299 x 299 x 3 to match the input specifications of the xception architecture. To ensure efficient data loading and transformation during the training phase, tensorflow's image generator was utilized for image preprocessing and augmen-tation.

The colors in each image were modified to fall within a prede-termined range, and this process was explained to emphasize the benefits of such normalization.

We will not accept it under any circumstances, regardless of the approach you take. We will not consider any approach that does not involve the inclusion of elements [0,1] using a scaling factor of 1/255. To improve the generalization and its capability to handle different lighting conditions, a brightness transformation was applied using a range of values from 0.8 to 1.2. This enhancement approach was not implemented for the validation set, but only for the training set. Furthermore, rescaling was only applied to the test set, without any augmen-tation, to guarantee the precision of the evaluation process. The dataset was divided into three subsets based on the division.

- The training set consisted of 32 batches, each with the addition of brightness augmentation.
- Validation set: filled with the same configuration of the training set to monitor the risk of overfitting.
- Test set: prepared with a batch size of 16 and executed without augmentation and shuffling to ensure accurate and unbiased evaluation.

2. ResNet50: To feed the brain MRI images into the convolutional neural network, all images were resized to 224 × 224 pixels, ensuring compatibility with the network's input specifications. Tensorflow's image generator was employed to preprocess images in real-time, facilitating efficient data loading and augmentation.

The images were modified to appear normal by adjusting the pixel values to fall within a specific range.

We will not accept any approach that does not involve them. We will not consider any approach that does not involve the inclusion of elements [0,1] using a rescaling factor of 1/255. To improve the model's ability to generalize and remain robust to variations in lighting conditions, brightness augmentation was applied during training and validation, using a range of brightness values from 0.8 to 1.2. Three subsets were formed from the dataset, with each subset having a specific configuration applied to it.

- The training set was enhanced with variations in bright-ness and divided into batches of 32 images for training.
- Validation set: augmented identically to the training set and also loaded in batches of 32 images.
- Test set: only normalized (without augmentation or shuf-fling), and loaded in batches of 16 images to ensure unbiased evaluation.

C. Model Architecture and Compilation

For this paper we are using two CNN models which are Xception and Resnet 50.here we can see the what are the

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parameters and attributes related to thier architecture.

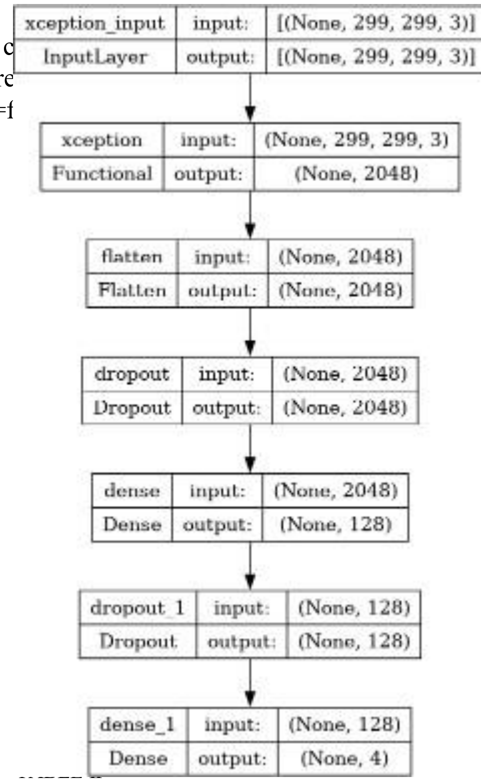
1. Xception The transfer learning technique was employed to c … s (glioma, meningioma, pituitary tumor, no tumor) by utilizing the xcep-tion architecture … s loaded with imagenet weights and excluded the top classi-fication layers (include_top=f … ; layer (pooling =’max’) to generate a fixed-length feature vector.

TABLE I
ARCHITECTURE OF THE PROPOSED DEEP LEARNING MODEL

Layer (Type)	Output Shape	Parameters
Xception (Functional)	(None, 2048)	20,861,480
Flatten	(None, 2048)	0
Dropout	(None, 2048)	0
Dense (ReLU)	(None, 128)	262,272
Dropout	(None, 128)	0
Dense (Softmax)	(None, 4)	516
Total Parameters		**21,124,268**
Trainable Parameters		**21,124,268**
Non-trainable Parameters		**0**

The transfer learning technique was employed to categorize brain MRI images into four groups (glioma, meningioma, pituitary tumor, no tumor) by utilizing the xception archi-tecture as the initial model. The base network was loaded with imagenet weights and excluded the top classification layers (include_top=false) and incorporated a global max pooling layer (pooling =’max’) to generate a fixed-length feature vector. The transfer learning technique was employed to categorize brain MRI images into four groups (glioma, meningioma, pituitary tumor, no tumor) by utilizing the xcep-tion architecture as the initial model. The base network was loaded with imagenet weights and excluded the top classi-fication layers (include_top=false) and incorporated a global max pooling layer (pooling =’max’) to generate a fixed-length feature vector.

2. Resnet 50: To comprehend the spread of data for the test, a group of 16 images was shown from the data generator. The images were showcased alongside their respective class labels, which were obtained by decoding one-hot encoded vectors using the generator’s internal mapping from class to index. The transfer learning approach was employed in the classification task, utilizing the pretrained resnet50 model that had been trained on the imagenet dataset. The model was built without its final layers of classification (include_top=false) and utilized global max pooling to reduce the output to a fixed 2048-dimensional feature vector. This was followed by a layer that was flattened and classified, which was a unique layer with 128 units and a relu activation function, with dropout layers (0.3, 0.25) inserted to prevent overfitting. The last layer of the network consisted of four neurons with a softmax activation function, allowing it to categorize the tumor types into glioma, meningioma, pituitary tumor, and no tumor classes. The model was constructed with the adamax optimizer with the learning rate of 0.001, categorical cross-entropy as the loss function



ARCHITECTURE OF THE PROPOSED CNN MODEL USING RESNET50

Layer (Type)	Output Shape	Parameters
ResNet50 (Functional)	(None, 2048)	23,587,712
Flatten	(None, 2048)	0
Dropout (rate=0.3)	(None, 2048)	0
Dense (128, ReLU)	(None, 128)	262,272
Dropout (rate=0.25)	(None, 128)	0
Dense (4, Softmax)	(None, 4)	516
Total Parameters		**23,850,500**
Trainable Parameters		**23,797,380**
Non-trainable Parameters		**53,120**

and baseline performance evaluation via accuracy, precision, and recall, which delivers a balanced measure of the quality of classification of all categories.

The process of building a model for architecture begins with a pre-trained resnet50 network which gets input images of dimension $224 \times 224 \times 3$ as input. This convolutional base extracts high level constructs and produces 2048 dimension vector. The extracted features are flattened and a dropout layer is applied in order to avoid overfitting. This then gets followed by another layer of 128 fully connected neurons with the relu activation function. To enhance generalization, another dropout layer is added. The last layer is densely connected layer where there are 4 units which are activated with softmax function and model is able to classify into 4 categories. This simple design exploits complicated feature embedding and somehow manages to make things simple on the classification head.

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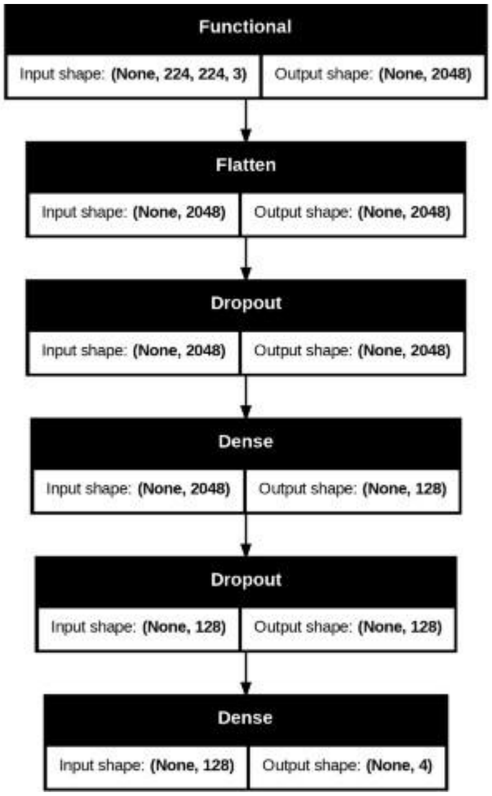

Fig. 3. Architecture of Renet 50

IV. Result

A. Xception Model

During the training, validation, and independent test sets, the performance of the proposed model was evaluated to determine its learning ability and ability to generalize. During training, the model achieved a final loss of 0.0158, with an impressive accuracy of 99.75%, demonstrating its ability to learn effectively from the training data and avoid overfitting. The validation results further support this finding, as the validation loss is minimal at 0.0902 and the accuracy is impressive at 98.76%. These figures illustrate that the model was able to apply its knowledge to new data without sacrificing its accuracy. To assess the model's real-world applicability, it was tested on a separate dataset that was not used during its development. Despite a slightly higher loss rate of 0.3500, the model achieved an impressive 98.48% accuracy score, demonstrating its effectiveness in classifying mri images. Despite consistently achieving accurate results, the increasing test loss suggests that the test set includes more challenging or ambiguous samples that the model struggled to predict correctly but with higher confidence levels. In conclusion, these results showcase the effectiveness of the resnet50-based architecture in performing the tasks of image classification and validating the suitability of the selected preprocessing, augmentation, and fine-tuning techniques.

TABLE III
XCEPTION MODEL PERFORMANCE ON TRAINING, VALIDATION, AND TEST SETS

Dataset	Loss	Accuracy (%)
Training	0.0158	99.75
Validation	0.0902	98.76
Test	0.3500	98.48

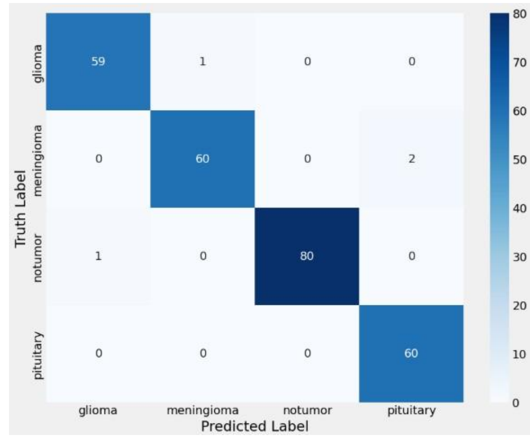

Fig. 4. Confusion matrix of the Xception-based model on the test set.

B. Resnet 50 Model

The model, which was inspired by the resnet50 architecture, consistently showcased outstanding performance throughout all stages of evaluation. Throughout the training phase, the model achieved a final loss of 0.0261 and an accuracy of 99.19%, showcasing successful learning and convergence. The validation set served as a standard for assessing the model's capacity to generalize, as the loss decreased to 0.0482 and the accuracy score reached 98.47%, indicating a lack of overfitting. The test set that was not used for training the model resulted in a loss of 0.0540 and an accuracy of 98.10%, demonstrating the model's ability to accurately predict data that it had not been exposed to during the training phase.

The difference between training and validation metrics is subtle, and when these metrics closely align with the perfor-mance of the test data, it indicates a well-regularized model that can effectively utilize its learned knowledge to analyze new, unfamiliar datasets. The low test loss also translates to confident predictions on difficult samples. These results confirm the model's dependability in terms of its structure, preprocessing pipeline, and training methodology, positioning it as a viable option for practical applications in automated brain MRI classification.

TABLE IV
MODEL PERFORMANCE ACROSS TRAINING, VALIDATION, AND TEST SETS

Dataset	Loss	Accuracy (%)
Training	0.0261	99.19
Validation	0.0482	98.47
Test	0.0540	98.10

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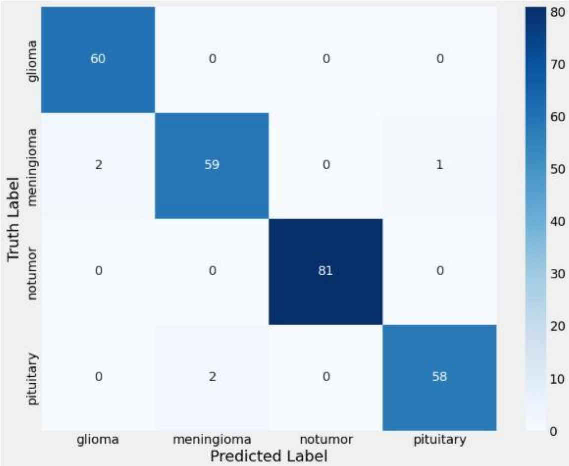

Fig. 5. Confusion matrix of the Resnet 50-based model on the test set.

C. Comparative Analysis

Two architectures of deep convolutional neural networks were compared for multi-class classification of brain MRI image: Xception, ResNet50. Both models were pretrained with ImageNet and fine-tuned with the same data, with the same preprocessing and augmentation scenario. Performance measures for training, validation, and test sets are as follow:

TABLE V
PERFORMANCE COMPARISON: ACCURACY BETWEEN XCEPTION AND RESNET50 MODELS

Model	Train Acc. (%)	Val Acc. (%)	Test Acc. (%)
Xception	**99.75**	**98.76**	**98.48**
ResNet50	99.19	98.47	98.10

TABLE VI
PERFORMANCE COMPARISON: LOSS BETWEEN XCEPTION AND RESNET50 MODELS

Model	Train Loss	Val Loss	Test Loss
Xception	0.0158	0.0902	0.3500
ResNet50	**0.0261**	**0.0482**	**0.0540**

By contrasting these two situations, several notable differ-ences and revelations become apparent.

Accuracy: xception performs better than resnet50 as regards the training set, with 99.75% and 99.19% respectively, and test set, at 98.48% and 98.10% respectively. This suggests that xception achieved better results in learning specific features related to its class, which could be attributed to its more intri-cate structure and the implementation of depthwise separable convolutions.

Although xception achieved higher accuracy, its test loss (0.3500) is significantly higher compared to resnet50 (0.0540). It implies that although xception had made accurate predic-tions, it had less confidence in its predictions, which may suggest that it was uncertain or overly confident in some misclassified samples.

The resnet50 model demonstrates exceptional generalization capabilities, particularly in terms of loss, when compared to other models, especially on the validation and testing sets. The slight difference in training and validation loss when using resnet50 suggests a more stable training process, minimizing the risk of overfitting.

Training efficiency: resnet50, which is a slightly shallower and more regularised architecture than xception, may have trained faster and required fewer resources, although this was not directly measured.

V. CONCLUSION

Both xception and resnet50 achieved exceptional results in classification, particularly on the brain MRI dataset, demon-strating the efficacy of transfer learning in medical image anal-ysis. The exception model achieved slightly higher accuracy across all datasets, suggesting a greater ability to capture in-tricate spatial hierarchies in the input images. Nevertheless, its higher test loss indicates a decrease in prediction accuracy or calibration, which can be detrimental in medical applications where certainty is of utmost importance.

Conversely, the resnet50 model achieved better results in terms of loss, particularly when it encountered unseen test data. Its lower test loss with the slight decrease in accuracy results in more stable, confident, and generalizable predictions. Thus, although xception might be more accurate, resnet50 strike a better balance between accuracy and robustness and therefore is safer to apply in working environments, especially if the overconfidence in wrong predictions have severe reper-cussions.

In conclusion, when accuracy is the utmost priority, xcep-tion will be the superior choice. Nevertheless, when precision, accuracy, and generalization are of utmost importance (which is often the case in healthcare), the resnet50-based model can be regarded as a more dependable and trustworthy decision-making tool.

REFERENCES

[1] S. Pereira, A. Pinto, V. Alves, and C. A. Silva, “Brain Tumor Segmenta-tion Using Convolutional Neural Networks in MRI Images,” *IEEE Trans. Med. Imaging*, vol. 35, no. 5, pp. 1240–1251, May 2016.

[2] B. Hemanth and M. Anitha, “Deep Learning-Based Brain Tumor Detec-tion and Classification Using ResNet50 and Xception Models,” *Comput. Biol. Med.*, vol. 131, p. 104248, Jan. 2021.

[3] A. Afshar, A. Mohammadi, M. Plataniotis, and K. N. Plataniotis, “Brain Tumor Type Classification via Capsule Networks,” *Proc. IEEE ICASSP*, pp. 1368–1372, 2019.

[4] D. Tandel et al., “A Review on a Deep Learning Perspective in Brain Tumor Classification and Segmentation,” *Comput. Biol. Med.*, vol. 131, p. 104248, Jan. 2021.

[5] H. Amin et al., “Brain Tumor Classification Based on Deep Fea-tures Extracted by ResNet50 and Xception,” *IEEE Access*, vol. 9, pp. 90112–90120, 2021.

[6] M. Aslam, T. Khan, and S. Khan, “Comparative Analysis of CNN Architectures for Brain Tumor Detection in MRI,” *IEEE Int. Conf. Bioinformatics and Biomedicine*, pp. 1180–1184, 2020.

[7] S. Jain, S. S. Tiwari, and M. M. Rathore, “Hybrid Deep Learning Model for Brain Tumor Detection Using MRI Images,” *Multimedia Tools Appl.*, vol. 80, pp. 8091–8107, 2021.

[8] A. Rehman et al., “Classification of Brain Tumor MRIs Using Deep Learning Based CNNs,” *Proc. IEEE Int. Conf. Eng. Tech. (ICET)*, pp. 1–6, 2020.

[9] K. Sajjad, S. Khan, A. Muhammad, H. K. Kim, and S. W. Baik, "Multi-Grade Brain Tumor Classification Using Deep CNN with Extensive Data Augmentation," *J. Comput. Sci.*, vol. 30, pp. 174–182, 2019.
[10] M. Hemanth, "Deep Learning in Brain Tumor Classification: A Com-parative Analysis Using Xception and Inception-v3," *Procedia Comput. Sci.*, vol. 167, pp. 2216–2223, 2020.
[11] P. Gumaei, M. Hassan, A. Alzahrani, "Hybrid Feature Extraction for MRI Brain Tumor Classification Using ResNet50," *IEEE Access*, vol. 7, pp. 178318–178328, 2019.
[12] M. P. Ismael and M. S. Abdel-Qader, "Brain Tumor Classification via Combined Deep CNNs and Transfer Learning," *J. Big Data*, vol. 7, no. 1, pp. 1–13, 2020.
[13] V. Khawaldeh, A. Tahir, et al., "Diagnosing Brain Tumor from MRI Using Hybrid Deep Learning Techniques," *Neural Comput. Appl.*, vol. 33, pp. 10925–10933, 2021.
[14] A. Lakkamraju and R. V. Kshirsagar, "Comparative Study of ResNet50 and VGG16 for Brain Tumor Detection," *Proc. Int. Conf. Comput. Commun. Secur.*, pp. 10–14, 2022.
[15] A. Mahajan and D. Agarwal, "Classification of Brain Tumor Using Transfer Learning and CNNs," *Int. J. Innov. Technol. Explor. Eng.*, vol. 9, no. 3, pp. 318–321, Jan. 2020.
[16] H. Islam and M. R. Hossain, "Brain Tumor Detection Using ResNet50 with Transfer Learning," *Int. J. Sci. Res. Eng. Dev.*, vol. 7, no. 2, pp. 51–56, 2021.
[17] K. Liu et al., "A Novel Approach to Brain Tumor Classification Using Deep Residual Networks," *IEEE Int. Conf. Bioinformatics*, pp. 201–207, 2019.
[18] R. Mehmood et al., "Brain Tumor Classification Using Deep Trans-fer Learning via Xception," *Multimed. Tools Appl.*, vol. 80, pp. 21087–21102, 2021.
[19] Y. Khan and N. Yousaf, "Classification of Brain Tumors Using Transfer Learning with Xception Network," *Proc. IEEE Int. Conf. Appl. Eng.*, pp. 145–149, 2020.
[20] M. Ashraf et al., "Transfer Learning for Brain Tumor MRI Classification Using ResNet and Xception," *IEEE Access*, vol. 9, pp. 56323–56333, 2021.