An Analysis of Transfer Learning Model for Deep Neural Network-based Automated Brain Tumor Diagnosis from MR Images

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Abstract. A crucial stage in the categorization of brain tumors for medical diagnosis and treatment. Magnetic resonance imaging (MRI) is routinely used to distinguish brain tumors; however, manual interpretation of the MRI data is arbitrary and time-consuming. In this work, we used transfer learning and the ResNet50 model with fine-tuning to classify brain tumor MR scans data into three different categories: meningioma, glioma, and pituitary tumors. Once the images had been pre-processed to lower noise and boost quality, they were then normalized and resized. The improved ResNet50 model achieved accuracy, precision, and recall, of 95.9%, 95.7%, and 95.19%. The results highlight the value of these techniques for analyzing medical images and demonstrate the potential for transfer learning and fine-tuning for the categorization of brain tumor MR images. This proposed study sets the framework for future research into the development of more sophisticated and effective techniques for categorizing MRI images of brain tumors.

Keywords: transfer learning, ResNet50, magnetic resonance images, brain tumor, classification, fine-tuning.

1 INTRODUCTION

Brain tumors are a significant public health issue across the world, and early identification and treatment can significantly improve patient outcomes. A common diagnostic technique for locating and classifying brain tumors is magnetic resonance imaging (MRI). In this work, we classified brain tumor MRI images into three categories using transfer learning and the ResNet50 model: meningioma, glioma, and pituitary.

As medical imaging data becomes more readily available, there is a growing demand for computer-aided methods to assist in the detection and treatment of brain tumors. The categorization of medical images using deep learning methods, notably transfer learning, has produced positive results. Transfer learning, which makes use of the knowledge gathered from a lot of data, allows a pre-trained model to be modified for a specific purpose.

R. Murugan et al. (eds.), *Proceedings of the International Conference on Signal Processing and Computer Vision (SIPCOV 2023)*, Advances in Engineering Research 239,
https://doi.org/10.2991/978-94-6463-529-4_19

In this work, we used transfer learning and the ResNet50 model to categorize brain tumor MRI data into three categories. During pre-processing, the dataset underwent denoising, normalization, and scaling to convert images into the .jpg format. The model's performance was evaluated using a confusion matrix, and measures including accuracy, precision, and recall. A graph of accuracy and loss versus epochs was used to visually depict the model's performance during the training phase.

By demonstrating how the ResNet50 model can classify MRI images of brain cancers via transfer learning, this work aimed to advance the field of medical imaging classification. The results of this study might contribute to the development of more accurate and efficient computer-aided methods for the diagnosis and treatment of brain cancer.

2 RELATED WORKS

Classifying a brain tumor is a crucial step in the medical diagnostic and treatment planning process. Due to its capability to provide finely detailed images of the brain's structure and tissue properties, imaging with magnetic resonance (MRI) is frequently used to distinguish brain cancers. Unfortunately, manual interpretation of MRI scans requires a lot of time and is subjective, necessitating automatic methods.

Several approches of computer vision and machine learning techniques over time to categorize MRI images of brain tumors. Based on manually created parameters, brain tumors have been categorized using conventional machine learning techniques like decision trees and support vector machines. For instance, K. Padmavathi et al. (2022), The authors of this article divided MRI into four kinds (glioma, no tumor, meningioma, pituitary). Using EfficientNet, they trained the architecture. The results showed that transfer learning performs effectively with small datasets [1].

Convolutional neural networks (CNNs), a type of deep learning technology, have recently been used to classify MRI images of brain tumors. These methods have demonstrated significant promise for automating categorization and reaching high accuracy rates. For instance, M. Arbane et al. (2020), In this study, the researcher put up a convolutional neural network as a deep learning model for classifying brain tumours from MRI images, CNN is based on transfer learning. The real system examines numerous CNN architectures, including ResNet, Xception, and MobilNet-V2. Although deep learning models occasionally need to be trained on enormous amounts of data, using these techniques with medical imaging datasets, which are often smaller, may be challenging [2].

Transfer learning has been used to categorize MRI images of brain tumors in to solve this problem. Transfer learning is taking a deep learning model that has already been trained and refining it on a smaller dataset so that it can learn the exact features necessary for the job at hand. In T. Mantha et al. (2021), research suggested using the EfficientNet-B3 deep learning architecture to automatically classify brain tumors in MRI data. This model can dissect MRI images of three different types of tumors: Glioma, pituitary, and meningioma tumors [3].

In T. Kanimozhi et. al, (2022) - The goal of the suggested study aims to develop a variational quantum circuit-based hybrid classical-to-quantum transfer learning approach that may be applied to MRI image-based brain tumor diagnosis. Using the pre-trained ResNet-18 CNN framework, this hybrid CNN-Quantum transfer learning model was created in an effort to achieve greater accuracy [4].

M. C. Xenya et. al, (2021) – this research showed three base learners techniques, two primary ensembles, and a final ensemble learner model make up the categorization model. Pre-trained VGG16, Inception-V3, and ResNet50 are used as basis learners to fine-tune the three base learners. [5].

J. Mathew et. al, (2022) - The main objective of this work is to examine the capacity of various transfer learning-based DCNN models that have been trained to recognize sick brain images. To help neurologists make prompt and informed judgments, this effort focuses on developing an efficient and trustworthy approach for identifying brain cancers using MRI. [6].

M. Mondal et. al, (2021) - In order to reliably identify three prevalent types of malignancies using brain MRI, on the basis of VGG-19, a deep transfer learning framework is presented in this paper. The recommended structure largely consists of two parts. The first phase is the VGG-19 frozen component, and the second phase is the modified neural style classification section [7].

Z. Chen et. al, (2022) - In this study, three CNN structures—MobileNet, EfficientNet, and ResNet—were used to evaluate four distinct transfer learning settings. The first preset employs a model without transfer learning, whereas the second preserves the learnability of all layers while using transfer learning, the third preset uses transfer learning while freezing the first 1/3 of layers, and the fourth preset uses transfer learning while freezing the first 2/3 of layers. The ImageNet dataset served as the training ground for all pre-trained models [8].

3 Proposed Methodology

3.1 Dataset

Here T1-weighted contrast-enhanced pictures of 3064 images consist of 708 slices each of meningioma, 1426 slices each of glioma, and 930 slices each of pituitary tumour from 233 individuals from the figshare.com.

3.2 Methodology

Pre-processing, transfer learning using ResNet50, fine-tuning, assessment, and visualization were some of the elements that made up the approach employed in this work. The parts that follow give a thorough explanation of each level. The flow chart of the proposed work has been shown in fig.1.

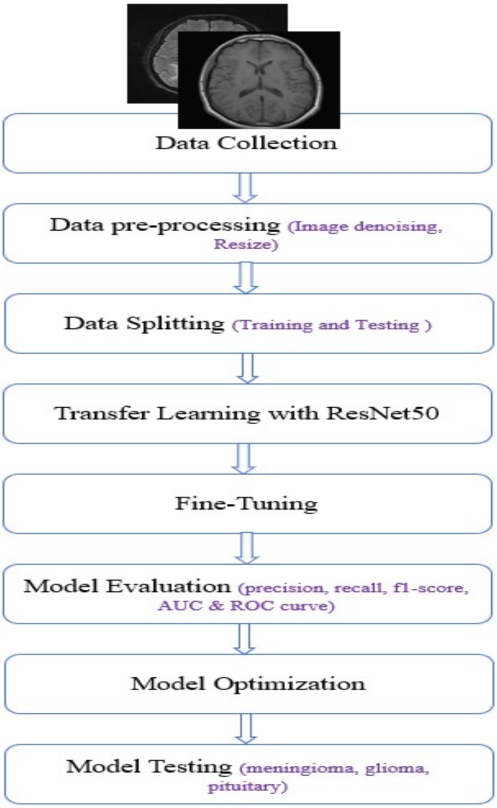


Fig. 1. Flow chart of the proposed work

1. Pre-processing: Prior to categorization, the MRI images underwent pre-processing to increase their uniformity and quality. The pre-processing procedures included denoising and normalization. These actions were taken to guarantee that the images had the same size and intensity distribution for the model to learn from and to eliminate any noise or artifacts that could have been present [9-11].

2. Transfer learning with ResNet50: The categorization of brain tumor MRI images uses transfer learning with ResNet50 as the basic model. Using the information gained from a sizable dataset on a related task, transfer learning entails optimizing a pre-trained model on a new task. The brain tumor MRI images dataset was used in this research work to fine-tune the pre-trained ResNet50 model.

3. Fine-tuning: The pre-trained ResNet50 model was fine-tuned to match the unique features of the brain tumor MRI images. This included changing the model's weights to minimize the loss function after training the model on the dataset of MRI scans of brain tumors. Combining backpropagation and gradient descent optimization methods was used for the fine-tuning procedure.

4. Evaluation: Several measures, including accuracy, precision, and recall were used to assess how well the refined ResNet50 model performed. These metrics give

information on how well the model can divide the scanned images into three categories of meningioma, glioma, and pituitary tumor.

5. Visualization: A confusion matrix, an accuracy, and a loss vs epochs graph were used to illustrate how well the refined ResNet50 model performed. These visualizations give a thorough overview of the model's performance and aid in pinpointing potential improvement areas.

Transfer learning:

A deep learning approach called transfer learning makes it possible to reuse a model that has already been trained for a different but related job. Transfer learning seeks to increase performance on a smaller, related job with little annotated data by utilizing the information gained from a big dataset on a comparable task.

Deep convolutional neural networks (DCNNs) have attained cutting-edge performance in the field of computer vision for a variety of applications like segmentation, object identification, and picture categorization. These models have mastered the ability to extract intricate and hierarchical characteristics from images after being trained on big datasets like ImageNet [12-14].

These pre-trained models may be improved for a particular task, like classifying MRI images of brain tumors, using transfer learning. By fine-tuning the pre-trained model, the model may utilize the information gained from the huge dataset and learn to adapt to the particular characteristics of the target task. In comparison to starting from scratch and training a model on a tiny dataset, this can lead to better performance and faster convergence [15].

ResNet50: The original ResNet design, which was created to solve the issue of vanishing gradients in very deep neural networks, has a variation called ResNet50.

The 50-layer ResNet50 architecture is intended to enable deep neural network training without experiencing vanishing gradient issues. This is accomplished by adding residual connections, which allow gradients to go freely through the network without being diluted by other layers.

ResNet50's residual connections enable the network to learn residual mapping or the distinction between a block of layers output and input. The network can skip over levels that might not be necessary for the present task by adding this residual mapping to the input of the following block of layers. With this method, incredibly deep neural networks that are more accurate than their shallower counterparts may be trained. In fig. 2., the block diagram of the proposed model has been shown.

A sizable dataset named ImageNet, which comprises over 1 million pictures and 1000 distinct classifications, was used to pre-train ResNet50. Transfer learning on other image recognition tasks, including object identification or segmentation, may be started with the pre-trained weights of ResNet50 [16-20].

ResNet50 is a potent neural network design that has been successful for a variety of computer vision tasks, in general. Its pre-trained weights make it a popular option for transfer learning, and its residual connections enable very accurate deep neural network training. We attempted to enhance the performance on the smaller and related tasks of brain tumor detection by fine-tuning the pre-trained ResNet50 model, using the information obtained from the vast dataset of natural images, and image categorization in MRI [21-25].

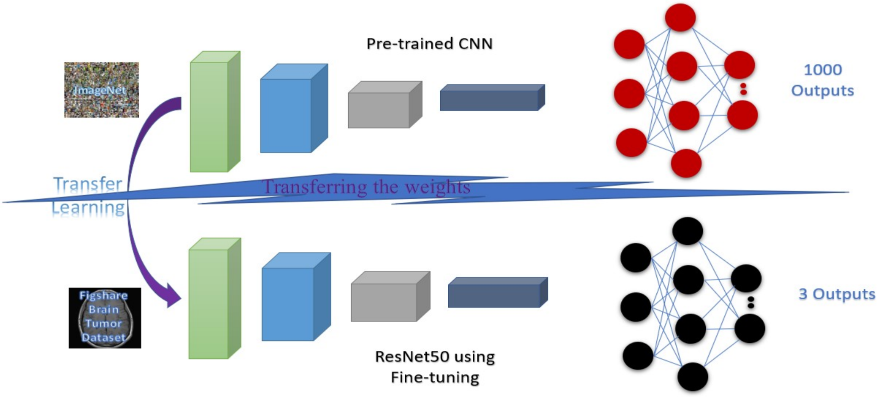


Fig. 2. Block diagram for the proposed model

4 Experimental Results

The study's findings demonstrated that the refined ResNet50 model could correctly divide the three types of brain tumors meningioma, glioma, and pituitary from the MRI scans. In fig.3. confusion matrix demonstrated that the model was capable of accurately classifying the vast majority of the images. The accuracy, precision, and recall of the model were computed.

In this study, 2451 images were taken for training and 613 images for testing purpose out of the total 3064 images.

22 epochs were used to evaluate the performance. 98.10% training accuracy and 95.90% test accuracy were attained after a total no. of iterations.

Fig. 4. (a) and (b) showed accuracy and loss vs. epochs graph also demonstrated how the loss reduced as the epoch count rose. This shows that the model was able to pick up new information and apply it effectively to the brain tumor image dataset of MRI.

According to the study's findings, it is possible to categorize brain tumor MRI scans into three different groups, including meningioma tumors, glioma tumors, and pituitary tumors, using transfer learning with ResNet50 and fine-tuning. High levels of accuracy, precision, and recall were attained by the refined ResNet50 model, demonstrating that it was able to pick up on the characteristics and patterns seen in the dataset of brain tumor MRI scans.

Contrasting the suggested transfer learning model and a few cutting-edge CNN algorithms is shown in the table. I. The same dataset, parameters, and settings were used for all of these models.

The table. I. makes it clear that the proposed model performed noticeably better than all the other models.

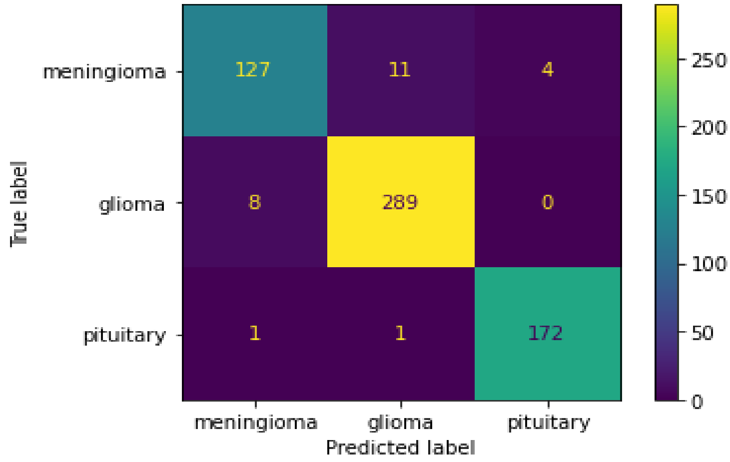
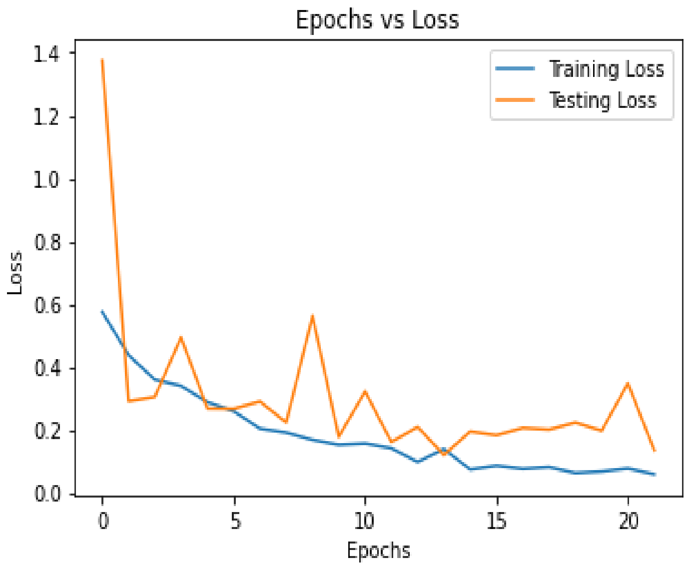
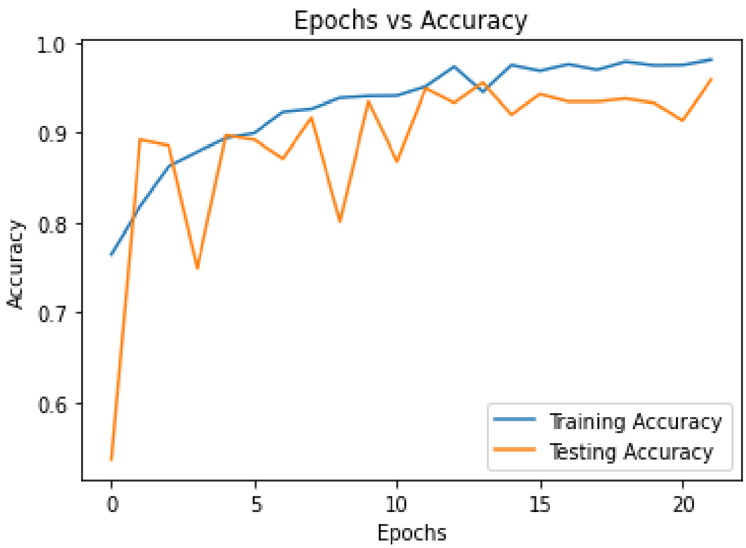


Fig. 3. Confusion Matrix for test images



(a)



(b)

Fig. 4. Graph between (a) Epochs vs Accuracy, and (b) Epochs vs Loss

Table 1. Performance Analysis

CNN Architectures	Accuracy	Precision	Recall
ResNet-50 [18]	93.23%	94.61%	92.19%
MobileNetV2 [14]	88.29%	89.62%	90.59%
Transfer Learning with VGG19 [7]	94.0%	94.0%	94.0%
Proposed work	**95.90%**	**95.70%**	**95.19%**

5 Discussion

The findings of the study show that the categorization of brain tumor MRI images into three categories meningioma, glioma, and pituitary can be accomplished by utilizing transfer learning with ResNet50 and fine-tuning approaches. High levels of accuracy, precision, and recall were attained by the refined ResNet50 model, demonstrating that it has learned the characteristics and patterns seen in the dataset of brain tumor MRI images.

The study emphasizes how transfer learning and fine-tuning may be used to analyze medical imaging data. The study's findings show that transfer learning has the potential to be utilized effectively for the interpretation of medical imaging data. Transfer learning has been applied successfully in a number of fields, incorporating natural language processing and computer vision. The study was able to overcome the drawbacks of utilizing a pre-trained model directly and reach a high degree of performance by fine-tuning the ResNet50 model.

The study's findings show that the model was able to pick up on the traits and patterns seen in the collection of MRI images of brain tumors. The model was able to attain a high degree of accuracy, and the graph of accuracy and loss vs epochs demonstrated that the loss reduced as the number of epochs grew. This shows that the model was able to adapt adequately to the dataset of brain tumor MRI images and learn.

6 Conclusion

In this work, transfer learning using ResNet50 and fine-tuning approaches were used to categorize brain tumor MRI scanes into three groups that are meningioma tumors, glioma, and pituitary tumors. The fine-tuned ResNet50 model achieved high levels of accuracy, precision, and recall proving the efficacy of transfer learning and fine-tuning for the interpretation of medical imaging data.

The results of the study demonstrate the efficacy of fine-tuning and transfer learning for the categorization of MRI images of brain cancers. The improved ResNet50 model was effective in generalizing the data and picking up on the traits and patterns present in the dataset of brain tumor MRI scans. The great performance and accuracy of the improved ResNet50 model show the promise of transfer learning and fine-tuning for the processing of medical imaging data.

The efficiency of fine-tuning techniques and transfer learning method on bigger and more diversified datasets of brain tumor MRI images may be evaluated in future studies. In this research, it is also possible to investigate the potential for newly trained models and refined methods for the processing of medical imaging data.

7 Acknowledgement

The researchers would like to convey their appreciation to the people and organizations that helped them with this study by lending their support and assistance.

The authors would like to thank their colleagues and peers for their constructive criticism and ideas, which helped to raise the calibre of our study.

References

1. Padmavathi, K., et al. "Transfer Learning Using EfficientNet for Brain Tumor Classification from MRI Images." 2022 International Conference on Computer Communication and Informatics (ICCCI). IEEE, 2022.
2. Arbane, Mohamed, et al. "Transfer Learning for Automatic Brain Tumor Classification using MRI Images." 2020 2nd International Workshop on Human-Centric Smart Environments for Health and Well-being (IHSH). IEEE, 2021.
3. T. Mantha and B. Eswara Reddy, "A Transfer Learning method for Brain Tumor Classification using EfficientNet-B3 model," CSITSS 2021 - 2021 5th Int. Conf. Comput. Syst. Inf. Technol. Sustain. Solut. Proc., pp. 2–7, 2021, doi: 10.1109/CSITSS54238.2021.9683036.
4. Kanimozhi, T., et al. "Brain Tumor Recognition based on Classical to Quantum Transfer Learning." 2022 International Conference on Innovative Trends in Information Technology (ICITIIT). IEEE, 2022.
5. Xenya, Michael Christopher, and Zenghui Wang. "Brain Tumour Detection and Classification using Multi-level Ensemble Transfer Learning in MRI Dataset." 2021 International Conference on Artificial Intelligence, Big Data, Computing and Data Communication Systems (icABCD). IEEE, 2021.
6. Mathew, Josmy, and N. Srinivasan. "Deep Convolutional Neural Network with Transfer Learning for Automatic Brain Tumor Detection from MRI." 2022 International Conference on Computing, Communication, Security and Intelligent Systems (IC3SIS). IEEE, 2022.
7. Mondal, Mrinmoy, et al. "Deep Transfer Learning Based Multi-Class Brain Tumors Classification Using MRI Images." 2021 3rd International Conference on Electrical & Electronic Engineering (ICEEE). IEEE, 2021.
8. Chen, Zhiyuan. "Study of Transferability of ImageNet-Based Pretrained Model to Brain Tumor MRI Dataset." 2022 International Conference on Machine Learning and Intelligent Systems Engineering (MLISE). IEEE, 2022.
9. Pacheco, Andre GC, Thomas Trappenberg, and Renato A. Krohling. "Learning Dynamic Weights for an Ensemble of Deep Models Applied to Medical Imaging Classification." 2020 International Joint Conference on Neural Networks (IJCNN). IEEE, 2020.
10. Uthra Devi, K., and R. Gomathi. "Retracted Article: Brain Tumour Classification using Saliency Driven Nonlinear Diffusion and Deep Learning with Convolutional Neural Networks (CNN)." Journal of Ambient Intelligence and Humanized Computing 12.6 (2021): 6263-6273.
11. Győrfi, Ágnes, Levente Kovács, and László Szilágyi. "Brain Tumor Detection and Segmentation from Magnetic Resonance Image Data using Ensemble Learning Methods." 2019 IEEE International Conference on Systems, Man and Cybernetics (SMC). IEEE, 2019.
12. Noreen, N., Palaniappan, S., Qayyum, A., Ahmad, I., Imran, M., & Shoaib, M. (2020). A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumor. IEEE Access, 8, 55135-55144.
13. Mzoughi, Hiba, et al. "Deep Multi-Scale 3D Convolutional Neural Network (CNN) for MRI Gliomas Brain Tumor Classification." Journal of Digital Imaging 33 (2020): 903-915.
14. Sandler, Mark, et al. "Mobilenetv2: Inverted Residuals and Linear Bottlenecks." Proceedings of the IEEE conference on computer vision and pattern recognition. 2018.

15. Sethy, Prabira Kumar, and Santi Kumari Behera. "A Data Constrained Approach for Brain Tumour Detection using Fused Deep Features and SVM." Multimedia Tools and Applications 80.19 (2021): 28745-28760.
16. Deepak, S., and P. M. Ameer. "Brain Tumor Classification using Deep CNN Features via Transfer Learning." Computers in biology and medicine 111 (2019): 103345.
17. Kumar, KS Ananda, A. Y. Prasad, and Jyoti Metan. "A Hybrid Deep CNN-Cov-19-Res-Net Transfer Learning Architype for an Enhanced Brain tumor Detection and Classification Scheme in Medical Image Processing." Biomedical Signal Processing and Control 76 (2022): 103631.
18. He, Kaiming, et al. "Deep Residual Learning for Image Recognition." Proceedings of the IEEE conference on computer vision and pattern recognition. 2016.
19. Nayak, Dillip Ranjan, et al. "Brain Tumour Classification using Noble Deep Learning Approach with Parametric Optimization through Metaheuristics Approaches." Computers 11.1 (2022): 10.
20. Mehrotra, Rajat, et al. "A Transfer Learning Approach for AI-based Classification of Brain Tumors." Machine Learning with Applications 2 (2020): 100003.
21. Y. Li and L. Shen, "Deep Learning based Multimodal Brain Tumor Diagnosis," in International MICCAI Brainlesion Workshop, pp. 149–158, Springer, 2017.
22. Seetha, J., and S. Selvakumar Raja. "Brain Tumor Classification using Convolutional Neural Networks." Biomedical & Pharmacology Journal 11.3 (2018): 1457.
23. F. Zhuang, et al. "A Comprehensive Survey on Transfer Learning." Proceedings of the IEEE, vol.109, 2020, pp. 43-76.international conference on computer vision. 2017.
24. Amin, Javeria, et al. "A New Approach for Brain Tumor Segmentation and Classification based on Score Level Fusion using Transfer Learning." Journal of medical systems 43 (2019): 1-16.
25. Swati, Zar Nawab Khan, et al. "Brain Tumor Classification for MR Images using Transfer Learning and Fine-Tuning." Computerized Medical Imaging and Graphics 75 (2019): 34-46.