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Brain Tumor Detection in MRI Images Using ResNet18 Convolutional Neural Network and Transfer Learning

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ABSTRACT

In this study, a deep learning-based brain tumor detection model is proposed using a Convolutional Neural Network (CNN) architecture, specifically the ResNet18 model. The aim is to develop an automated and accurate system capable of detecting brain tumors from MRI images, classifying them into two categories: “tumor present” and “no tumor.” To enhance performance and reduce the need for large-scale annotated medical datasets, the model employs transfer learning by initializing with pre-trained weights from the ImageNet dataset. The final fully connected layers of the ResNet18 network are fine-tuned to adapt to the specific binary classification task. The MRI dataset is divided into training and test sets, and preprocessing steps such as image resizing and normalization are applied to standardize inputs. After training for ten epochs, the model achieved promising results, including an accuracy of 84.31%, a precision of 79.31%, a recall of 92.00%, and an F1 score of 85.19%. These metrics indicate the model’s robustness in detecting tumors with high sensitivity and specificity. The experimental results suggest that the proposed method can effectively extract and interpret critical features from MRI scans, offering a reliable tool for assisting radiologists in early diagnosis and reducing the risk of human error in clinical decision-making.

1. INTRODUCTION

Brain tumor detection is considered one of the most important challenges in modern medicine because brain tumors can grow rapidly and damage various parts of the brain. Timely and accurate detection of these tumors can significantly improve the patient's quality of life and also assist the medical team in designing the best treatment plan [1].

Medical imaging techniques, particularly Magnetic Resonance Imaging (MRI), are essential tools for detecting brain tumors. These images clearly display different structures and tissues of the brain, allowing physicians to identify brain abnormalities, including tumors. However, the large volume and complexity of MRI images make manual analysis and tumor detection a time-consuming and sensitive process. At the same time, this process is highly dependent on the physician's experience and knowledge, which can lead to errors and individual variations in

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diagnosis. Therefore, the development of automatic methods that can accurately detect brain tumors is of great importance [2].

In recent years, deep learning has emerged as one of the most advanced branches of machine learning due to its ability to process large amounts of data and extract complex features. One of the popular models in deep learning for image processing is Convolutional Neural Networks (CNNs), which are widely used in detecting image abnormalities, including brain tumors. CNNs, due to their layered structure and ability to identify various features from simple to complex patterns, are recognized as one of the best models for medical image analysis. These networks can extract important features like edges, textures, and shapes from images and make precise decisions based on them [3-4].

Among the different CNN models, the ResNet model stands out due to its depth and unique architecture that uses the concept of residual connections. ResNet, introduced by He et al. in 2015, addresses the vanishing gradient problem that typically occurs in deep networks through the use of residual connections. This feature allows ResNet to use deeper layers and, as a result, identify more complex features in the data. Additionally, ResNet is one of the models that can be used in transfer learning, meaning the model can transfer knowledge gained from large datasets to new problems, reducing the need for training from scratch. Transfer learning is especially important in fields where labeled data is scarce, such as medical images. This study utilizes the ResNet model for brain tumor detection based on MRI images. The data used in this study is from the Brain Tumor MRI Dataset from Kaggle, which includes MRI images from patients with brain tumors as well as healthy individuals. This data is split into training and test sets, and the ResNet model is trained to identify the presence or absence of tumors in the images. One of the advantages of using ResNet in this study is the ability to fine-tune the final layers of the model to classify the two categories "tumor present" and "tumor absent." This research includes steps such as data preprocessing, model training, model accuracy evaluation, and result analysis. During preprocessing, the data is resized and normalized to make it compatible with the model.

2. LITERATURE REVIEW

This study investigates deep CNN models for brain tumor classification. CNNs are used in this research to accurately detect various types of brain tumors from MRI images. The results demonstrate the high efficiency of CNNs in detecting complex image patterns, and methods to improve accuracy and reduce errors have been utilized. The authors show that deep CNN models perform well in medical image classification tasks, particularly in brain tumor classification [1].

This article reviews CNN techniques for brain tumor classification from 2015 to 2022 and discusses challenges and future prospects. The authors emphasize the importance of different CNN architectures and highlight challenges such as data imbalance, image quality, and model learning issues. The paper also compares the performance of CNN models against other machine learning methods and highlights the role of these models in improving diagnostic accuracy [2].

In this article, researchers used CNNs to classify brain tumors in MRI images. The proposed method includes a CNN architecture specifically designed for brain tumor detection, and the results show that this method can detect brain tumors at early stages with high accuracy and efficiency. This study offers a significant improvement in detection accuracy compared to traditional methods [3].

This article focuses on brain tumor classification using CNNs. The researchers showed that their proposed CNN model could identify brain tumors with high accuracy by analyzing MRI images. The paper discusses the optimization of networks to improve detection accuracy and compares the model's performance with other methods [4]. In this study, a new method for detecting brain tumors based on the combination of CNN and Bayesian optimization is proposed. The researchers used Bayesian optimization to tune the parameters of the CNN, resulting in improved detection accuracy and reduced model error. This approach has reduced training time and optimized network architecture, providing better performance and accuracy [5].

This study uses a multi-scale CNN for brain tumor classification and segmentation. The proposed architecture includes a multi-layer, multi-scale model that processes data simultaneously at different scales, helping improve model accuracy and sensitivity. The paper discusses the effectiveness of the multi-scale method in identifying various patterns in MRI images [6].

This paper proposes a new CNN model for brain tumor classification. The model is designed to analyze complex features in MRI images, enabling it to detect brain tumors with greater precision. The paper provides details on model optimization and settings, highlighting the advantages of the new approach compared to traditional networks [7]. This paper automatically classifies brain tumors from MRI images using CNN features and Support Vector Machines (SVM). The proposed model extracts CNN features and uses them for classification with SVM, resulting in significant improvements in accuracy and speed [8].

This study employs an optimized CNN for multi-class brain tumor image classification and compares its performance with other models. The proposed model, with optimized CNN settings and parameters, achieves better performance in detecting various types of tumors [9].

In this study, researchers used a new activation function called Flatten-p Mish in the CNN architecture for brain tumor classification. This activation function enhances model accuracy and speed, increasing the model's performance in identifying complex image patterns [10].

This paper compares various CNN models for brain tumor classification and evaluates their performance. The results show that CNN models play a crucial role in improving detection accuracy and reducing diagnostic errors [11].

This paper introduces a robust method for brain tumor classification using CNN, demonstrating superior performance compared to other models. This method is also applicable to complex and large datasets, providing high accuracy [12].

In this study, deep learning is used for brain tumor classification. Researchers have designed an efficient CNN that provides high accuracy in detecting brain tumors from MRI images [13].

3. METHODOLOGY

The proposed methodology for this research consists of several key stages, implemented cohesively and step-by-step to develop a brain tumor detection model based on MRI images using the ResNet neural network. In the first stage, the data used in this study were obtained from the Brain Tumor MRI Dataset on Kaggle, which includes MRI images from patients with brain tumors as well as healthy individuals. This dataset is divided into two main categories, namely, images with tumors and images without tumors.

After obtaining the data, the data preprocessing process begins. This stage involves several crucial processes aimed at improving data quality and ensuring compatibility with the ResNet neural network model. To achieve this, the images are resized to a standard size to match the input dimensions required by ResNet. Then, the data is normalized based on the mean and standard deviation, ensuring that pixel values fall within a suitable range, allowing the model to better learn image features. Furthermore, data augmentation techniques such as random horizontal flipping and rotational changes are applied to increase data diversity and reduce the risk of overfitting.

Next, the data is split into two sets: training and testing, with 80% of the data allocated for training and 20% for testing. This split allows the model to learn patterns from the training data and subsequently evaluate its performance on the testing data.

Once the data is prepared, the ResNet18 model, which is a pre-trained convolutional neural network, is employed for this task. ResNet18 is well-suited for learning complex features and can identify the relevant structures in MRI images. This model, which has been pre-trained on the large ImageNet dataset, is used in transfer learning, meaning its weights are retained, and only the output layers are modified to fit the current task. Specifically, the final fully connected layer of the ResNet model is configured to produce two output neurons, one for the "tumor present" class and the other for the "tumor absent" class.

For training this model, the cross-entropy loss function is used to minimize the discrepancy between the model's predictions and the actual values. The Adam optimizer is chosen, as it is capable of updating weights efficiently and improving convergence speed. During the training phase, the training data is fed into the model, which attempts to make accurate predictions by updating its weights. After each epoch, the model's performance is evaluated by calculating the average training error to ensure gradual improvement. After training completion, the model is evaluated on the test data.

Below is a table outlining the structure of the proposed ResNet18 model for brain tumor detection, including the layers and their parameters:

Table 1. Structure of the Proposed Network

Layer	Layer Type	Output Dimensions	Details
1	Conv2d	64x112x112	Kernel: 7x7, Stride: 2, Padding: 3
2	MaxPool2d	64x56x56	Kernel: 3x3, Stride: 2
3	Residual Block (2 layers)	64x56x56	Two 3x3 convolution layers with 64 filters and residual connections
4	Residual Block (2 layers)	128x28x28	Two 3x3 convolution layers with 128 filters and residual connections, Stride: 2 in the first block
5	Residual Block (2 layers)	256x14x14	Two 3x3 convolution layers with 256 filters and residual connections, Stride: 2 in the first block
6	Residual Block (2 layers)	512x7x7	Two 3x3 convolution layers with 512 filters and residual connections, Stride: 2 in the first block
7	Average Pooling	512x1x1	Kernel: 7x7
8	Fully Connected (FC)	2	Number of neurons: 2 (final classification for detecting "tumor present/absent")

This table summarizes the layers of the ResNet18 architecture used for brain tumor detection, detailing each layer's type, output dimensions, and key parameters. The network is designed to progressively extract features through convolutional layers and residual blocks, eventually performing classification based on the final fully connected layer.

Fig. 1. Training Process of the Network with Iterations

4. EXPLANATION OF THE EVALUATION METRICS CHART

The Evaluation Metrics chart shows the final values for four performance evaluation metrics of the model: Accuracy, Precision, Recall, and F1 Score. These values were obtained after completing the training process and evaluating the model on the test data.

- Accuracy of the model is around 0.8431, indicating the overall percentage of correct predictions made by the model.

- Precision is about 0.7931, which indicates the proportion of positive predictions that were truly positive.
- Recall is 0.9200, representing the percentage of actual positive cases that the model correctly identified.
- F1 Score, with a value of 0.8519, is the harmonic mean of Precision and Recall, demonstrating the model's balanced performance between these two metrics.

These results reflect the model's strong performance in detecting and classifying brain tumors, highlighting its high accuracy and sensitivity when evaluating new data.

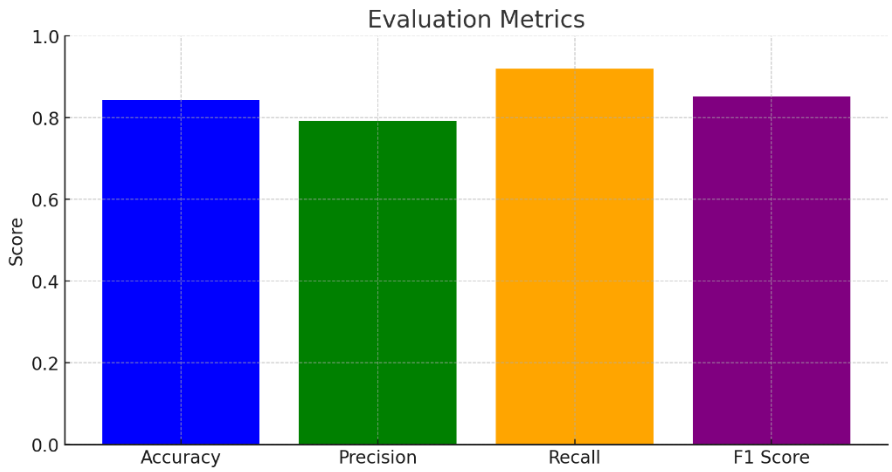

Fig. 2. Performance Specifications

5. CONCLUSION

This study demonstrated that the use of the ResNet18 convolutional neural network, leveraging transfer learning, can serve as an effective tool for detecting brain tumors in MRI images. The proposed model, after training and optimization, achieved high accuracy and favorable evaluation metrics, including Accuracy, Precision, Recall, and F1 Score. These results indicate that ResNet18 is capable of identifying complex patterns in MRI images and detecting brain tumors with high precision.

Overall, the findings of this study highlight the significant potential of deep learning models in the automatic detection of complex diseases like brain tumors. These models can serve as valuable tools in medical diagnostics, aiding in the early detection of diseases and reducing the workload of healthcare professionals. Furthermore, by reducing diagnostic errors, this model can play a crucial role in enhancing the accuracy and efficiency of diagnostic systems in the medical field.

Declaration

We acknowledge that we used ChatGPT to enhance the academic writing of our manuscript while ensuring the originality and integrity of our work.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

The authors declare that they have no competing interests.

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REFERENCES

[1] Ayadi, W., Elhamzi, W., Charfi, I., & Atri, M. (2021). Deep CNN for brain tumor classification. Neural Processing Letters, 53, 671–700. https://doi.org/10.1007/s11063-020-10398-2

[2] Xie, Y., Zaccagna, F., Rundo, L., Testa, C., Agati, R., Lodi, R., ... & Tonon, C. (2022). Convolutional neural network techniques for brain tumor classification (from 2015 to 2022): Review, challenges, and future perspectives. Diagnostics, 12(8), 1850. https://doi.org/10.3390/diagnostics12081850

[3] Khan, H. A., Jue, W., Mushtaq, M., & Mushtaq, M. U. (2020, September 15). *Brain tumor classification in MRI image using convolutional neural network*. *Mathematical Biosciences and Engineering, 17*(5), 6203–6216. https://doi.org/10.3934/mbe.2020328

[4] Agarwal, A. K., Sharma, N., & Jain, M. K. (2021, January). *Brain tumor classification using CNN*. *Advances and Applications in Mathematical Sciences, 20*(3), 397–407.

[5] Ait Amou, M., Xia, K., Kamhi, S., & Mouhafid, M. (2022, March). A novel MRI diagnosis method for brain tumor classification based on CNN and Bayesian optimization. In Healthcare (Vol. 10, No. 3, p. 494). MDPI. https://doi.org/10.3390/healthcare10030494

[6] Díaz-Pernas, F. J., Martínez-Zarzuela, M., Antón-Rodríguez, M., & González-Ortega, D. (2021). A deep learning approach for brain tumor classification and segmentation using a multiscale convolutional neural network. Healthcare, 9(2), 153. https://doi.org/10.3390/healthcare9020153

[7] Ayadi, W., Elhamzi, W., & Atri, M. (2020, December). A new deep CNN for brain tumor classification. In 2020 20th International Conference on Sciences and Techniques of Automatic Control and Computer Engineering (STA) (pp. 266–270). IEEE. https://doi.org/10.1109/STA50679.2020.9329328

[8] Deepak, S., & Ameer, P. M. (2021). Automated categorization of brain tumor from MRI using CNN features and SVM. Journal of Ambient Intelligence and Humanized Computing, 12(8), 8357–8369. https://doi.org/10.1007/s12652-020-02568-w

[9] Irmak, E. (2021). Multi-classification of brain tumor MRI images using deep convolutional neural network with fully optimized framework. Iranian Journal of Science and Technology, Transactions of Electrical Engineering, 45(3), 1015–1036. https://doi.org/10.1007/s40998-021-00426-9

[10] Mondal, A., & Shrivastava, V. K. (2022). A novel parametric flatten-p Mish activation function based deep CNN model for brain tumor classification. Computers in Biology and Medicine, 150, 106183. https://doi.org/10.1016/j.compbiomed.2022.106183

[11] Hussain, T., Ullah, A., Haroon, U., Muhammad, K., & Baik, S. W. (2021). A comparative analysis of efficient CNN-based brain tumor classification models. In Generalization with Deep Learning: For Improvement on Sensing Capability (pp. 259–278). https://doi.org/10.1142/9789811218842_0011

[12] Tazin, T., Sarker, S., Gupta, P., Ayaz, F. I., Islam, S., Monirujjaman Khan, M., ... & Alshazly, H. (2021). [Retracted] A robust and novel approach for brain tumor classification using convolutional neural network. Computational Intelligence and Neuroscience, 2021(1), 2392395. https://doi.org/10.1155/2021/2392395

[13] Saleh, A., Sukaik, R., & Abu-Naser, S. S. (2020, August). Brain tumor classification using deep learning. In 2020 International Conference on Assistive and Rehabilitation Technologies (iCareTech) (pp. 131–136). IEEE. https://doi.org/10.1109/iCareTech49914.2020.00032