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ORIGINAL ARTICLE

Enhanced Brain Tumor Classification using Modified ResNet50 Architecture

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ABSTRACT - Accurate classification of brain tumors is crucial for precise medical diagnosis and treatment planning. This paper presents an innovative approach to brain tumor classification using a modified ResNet50 architecture. The methodology combines data preprocessing, architectural enhancements, and rigorous performance evaluation to achieve robust classification results. The proposed model is developed through the modification of ResNet50, tailored to capture intricate features in brain tumor images. Comparative analysis against established architectures, including AlexNet, GoogleNet, ResNet18, and ResNet50, is conducted using accuracy, sensitivity, specificity, and precision as evaluation metrics. The results underscore the superiority of the proposed model in accurately classifying brain tumor instances. This study contributes to the advancement of brain tumor classification techniques and the enhancement of medical image analysis methods.

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INTRODUCTION

Brain tumor classification is a pivotal task in medical imaging analysis, aiding clinicians in accurate diagnosis and treatment planning. In recent years, the advent of deep learning techniques has ushered in new possibilities for automating and improving the accuracy of this classification process. However, the search for an accurate deep learning model for brain tumor detection is still an ongoing research endeavor. While the convolutional neural network (CNN) is commonly used for detecting brain tumors, the specific CNN model that is most accurate still remains unknown. This paper introduces a comprehensive methodology that includes architecture enhancement and performance evaluation to achieve robust brain tumor classification.

The methodology outlined in this study employs a systematic approach to address the challenges inherent in brain tumor classification. Specifically, the study focuses on enhancing the ResNet50 architecture through the integration of additional layers and resizing techniques.

The core contribution of this study lies in the proposed model enhancement based on the ResNet50 architecture. This enhancement involves the integration of additional convolutional layers, the application of batch normalization, and the use of the Rectified Linear Unit (ReLU) activation function. These refinements are meticulously executed to augment the architecture's capacity to capture intricate features and patterns in brain tumor images.

The remainder of this paper is organized as follows: Section 2.0 discusses the related works of this study. Section 3.0 elaborates on the methodology employed in this study. Section 4.0 presents the results and discussions. Finally, Section 5.0 concludes this paper. Through this comprehensive methodology, the paper aims to contribute to the advancement of brain tumor classification techniques and pave the way for further innovations in medical image analysis.

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RELATED WORKS

Several previous papers have been published that uses computer vision techniques to detect brain tumor from Magnetic Resonance Imaging (MRI) images. For example, Siontis et al. [1] focuses on Primary Cardiac Sarcoma (PCS) and its prognosis, with a particular emphasis on factors that contribute to its poor outcome. The research conducted a retrospective analysis of medical records from the University of Michigan, spanning the years 1992 to 2017, to understand the disease better. The study encompassed 39 patients with PCS, primarily affecting individuals with a median age of 41 years. Common histological types included angiosarcoma, high-grade undifferentiated pleomorphic sarcoma, and leiomyosarcoma. Tumors were frequently found in the left atrium and right atrium, and their location often correlated with tumor type. Many patients presented with metastases, commonly involving the lungs, bones, liver, and brain. Surgical resection was attempted in a portion of cases, leading to varying outcomes. The median overall survival for patients was 12.1 months. The study also highlighted the relationship between brain metastases and left heart tumors, indicating a higher risk of brain metastases in such cases. The findings underscore the challenging prognosis of PCS, with limited treatment options, late-stage diagnoses, and a significant risk of brain metastases. As a result, the study suggests the need for increased awareness among medical practitioners about the heightened risk of brain metastases and the consideration of brain imaging during diagnosis and follow-up.

Özyurt et al. [2] addresses the challenging task of brain tumor classification in medical image processing. They introduces a novel approach called Neutrosophy and Convolutional Neural Network (NS-CNN) for this purpose. The goal is to distinguish between benign and malignant tumor regions segmented from brain images. The study comprises two main stages: segmentation using the NS-EMFSE approach and classification using Convolutional Neural Network (CNN) features with SVM and KNN classifiers. Evaluation was conducted through 5-fold cross-validation on 160 tumor instances (80 benign and 80 malignant). The results showed that CNN features achieved high classification performance with both SVM and KNN classifiers. Particularly, SVM with CNN features demonstrated superior performance, with an average success rate of 95.62%. The study highlights the effectiveness of the proposed NS-CNN hybrid method in accurately classifying brain tumor regions and showcases the potential of CNN features in enhancing classification outcomes.

Sharma et al. [3] focuses on automated defect detection in medical imaging, particularly in the context of tumor detection in MRI. The traditional approach of human inspection for defect detection, such as tumor identification in MRI brain images, is impractical for large datasets. Therefore, automated methods have emerged to save time and assist radiologists. Tumor detection in MRI brain images is challenging due to the complex nature and variations of tumors. This paper presents a solution that employs machine learning algorithms for brain MRI tumor detection. The approach involves three main steps: preprocessing of MRI images, extraction of texture features using Gray Level Co-occurrence Matrix (GLCM), and classification using machine learning algorithms. This methodology aims to automate the tumor detection process, addressing the challenges associated with manual inspection and the complexities of MRI brain tumor identification.

Seetha et al. [4] presents an automatic brain tumor classification approach using CNNs based on MRI images. Brain tumors are aggressive and life-threatening, necessitating accurate diagnosis and treatment planning. The abundance of MRI data makes manual classification impractical, prompting the development of an automated method. The proposed CNN architecture, designed with compact kernels and small neuron weights, achieves a high accuracy rate of 97.5% with low complexity. This method surpasses other state-of-the-art techniques, effectively addressing the challenge of classifying brain tumors amidst the diverse spatial and structural variations in the surrounding brain regions.

Amin et al. [5] focuses on the early detection of brain tumors using MRI to enhance patient survival rates. The research employs a multi-step approach: Weiner filtering with different wavelet bands to enhance input slices, Potential Field (PF) clustering to identify tumor pixels, global thresholding and mathematical morphology operations to isolate tumor regions in Fluid Attenuated Inversion Recovery (FLAIR) and T2 MRI images. For accurate classification, Local Binary Pattern (LBP) and Gabor Wavelet Transform (GWT) features are combined. Evaluation metrics such as peak signal-to-noise ratio (PSNR), mean squared error (MSE), and structured similarity index (SSIM) are utilized, resulting in promising results for both T2 and FLAIR MRI images. The approach is assessed based on pixel-level segmentation and fused feature-based segmentation, achieving high precision, sensitivity, accuracy, and Dice similarity coefficient (DSC) on various datasets. Overall, the proposed approach demonstrates significant improvements over existing methods in brain tumor segmentation and detection.

Bingol et al. [6] focuses on utilizing deep learning architectures to analyze big data, which encompasses various forms of information like videos, photos, and text collected from diverse sources about a specific topic. The research aims to enhance early diagnosis of brain tumors, a critical and life-threatening condition, to improve patient survival rates. The study employs deep learning models including AlexNet, GoogleNet, and ResNet50 to detect brain tumor images. Among these architectures, ResNet50 achieved the highest accuracy rate of 85.71%. The study acknowledges the potential for further improvement and plans to develop a novel CNN based method to achieve even higher accuracy than existing deep learning approaches. The goal is to enhance early diagnosis capabilities for brain tumors and contribute to medical advancements.

El-Feshawy et al. [7] discusses the significance of early brain tumor detection due to its potential life-threatening nature and rising prevalence. The authors explore detection methods using deep learning and IoT technologies. Two scenarios are presented: one involves applying a deep CNN directly to brain images, and the other introduces an IoT-based framework with cloud-based multiuser detection. A ResNet18 CNN model is proposed, optimized through experiments with various parameters. The suggested model achieves a high accuracy of 98.67%, outperforming traditional CNNs. The study emphasizes the importance of these advancements in enhancing brain tumor detection and patient outcomes.

With the evolution of deep learning in medical image analysis, numerous pre-trained models have been assessed for brain tumor detection. However, there is room for further improvement in these pre-trained models by modifying their networks to achieve better outcomes. Additionally, the utilization of depth concatenation in pre-trained models for precise detection is not widespread. Depth concatenation is advantageous for augmenting the feature maps of deep learning models, thereby enhancing detection accuracy. This paper presents an enhanced version of ResNet50 through the incorporation of a depth concatenation layer, resulting in improved brain tumor detection accuracy. The main contribution of this study lies in the proposal of an improved ResNet50 variant that outperforms the original ResNet50 and surpasses other deep learning models commonly employed for brain tumor detection.

METHODOLOGY

The methodology employed in this study outlines a systematic approach to address brain tumor classification through deep learning techniques. The process encompasses data collection from Kaggle datasets, followed by essential preprocessing steps including image resizing for compatibility with various architectures. The dataset is then partitioned into training and testing sets, and pre-trained models such as AlexNet [8], GoogleNet [9], ResNet18 [10], and ResNet50 [10] are adapted for binary classification by modifying their final layers. Additionally, a model based on an enhanced ResNet50 architecture is proposed, involving the integration of additional layers and resizing techniques. The proposed model is trained and subsequently evaluated using performance metrics like accuracy, sensitivity, specificity, and precision. A comparative analysis is conducted, benchmarking the proposed model against other established architectures. This methodology provides a structured framework to comprehensively investigate brain tumor classification, ensuring consistent and replicable experimental procedures. Figure 1 shows the block diagram of the methodology.

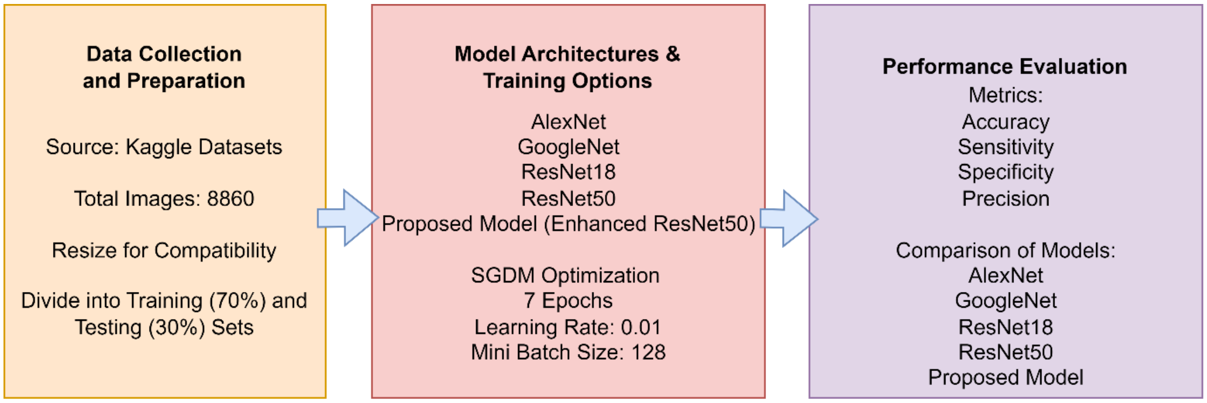
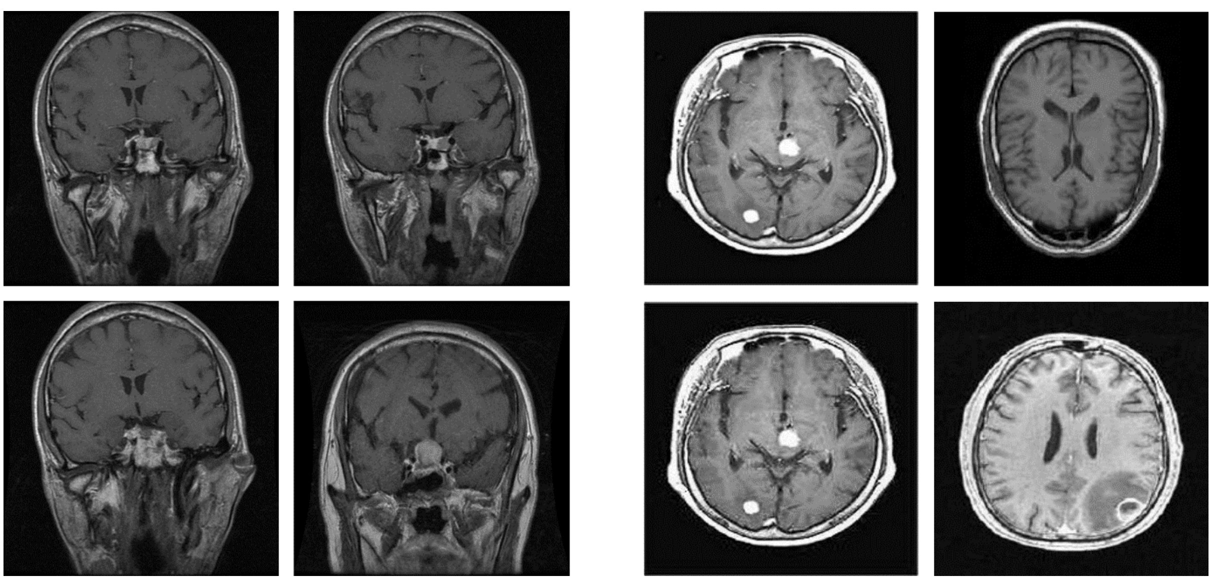


Figure 1. The Block Diagram Of The Methodology

DATA COLLECTION AND IMAGE PREPARATION

The experiments were carried out using MATLAB 2023, utilizing brain tumor images sourced from the Kaggle datasets [11]. The datasets obtained comprised a total of 8860 images, each with varying dimensions and no fixed aspect ratio. To ensure compatibility with different deep learning architectures, all images were uniformly resized. Specifically, images were resized to 224×224 pixels for ResNet18, ResNet50, GoogleNet, and the proposed model, while for AlexNet, images were resized to 227×227 pixels. To facilitate experimentation, the dataset was divided into a training set and a testing set. The training set encompassed 70% of the total data, with the remaining 30% forming the testing set. Solely the training set was used for the training of all deep learning models. Following the training phase, the models were evaluated using the testing set to gauge their performance. Figure 2 depicts a selection of images acquired from the dataset.



(a) (b)

Figure 2. Various MRI brain images extracted from the dataset. (a) Images featuring brain tumors (positive). (b) Images without brain tumors (negative).

THE PROPOSED MODEL

The central innovation revolves around the upgrading of the ResNet50 architecture. Enhancements were introduced through the incorporation of a convolutional layer, the application of batch normalization for improved outcomes, and the utilization of the ReLU activation function. The ReLU function eliminates all the negative pixels in a feature image. By discarding these negative pixels, the model can focus on learning the relevant features associated with brain tumors, rather than being hindered by irrelevant features unrelated to brain tumors. These modifications were executed with meticulous attention to detail, aiming to transcend the established framework of ResNet50. Following the application of the ReLU activation, the resulting output underwent a deliberate resizing procedure. Subsequently, the resized feature maps were judiciously integrated with the original ResNet50 output, leading to a substantial adjustment in the architecture.

To tailor the model for the specific demands of the binary classification task, a freshly devised fully connected layer was introduced and connected to the aforementioned amalgamated output. In terms of model training, the Stochastic Gradient Descent with Momentum (SGDM) optimization technique was selected due to its capability to expedite the learning process and skillfully navigate the intricacies of training dynamics.

With these refinements in effect, the model underwent a training regimen spanning 7 epochs, during which the internal parameters were systematically fine-tuned, guided by a learning rate of 0.01. The salient attribute of novelty lies in the orchestrated transformation of ResNet50 through a sequence of deliberate and tactful adjustments. This culminated in the development of a model poised to excel proficiently within the distinctive domain of the two-class classification task. The modifications implemented in the ResNet50 model to enhance its performance are visually presented in Figure 3.

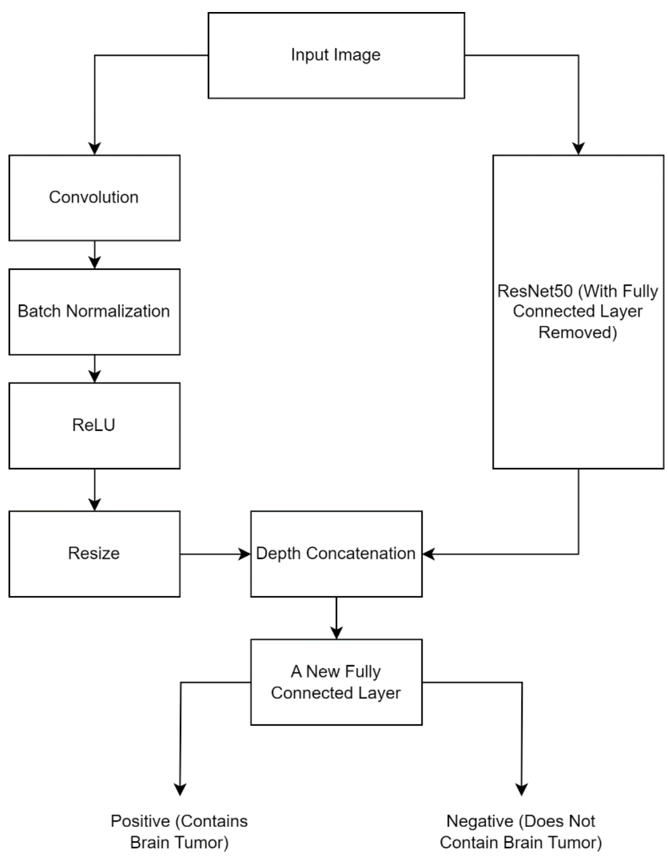


Figure 3. The proposed model (modified ResNet50).

The modified ResNet50 has seen improvements, expanding its capabilities well beyond its original framework. The original ResNet50 architecture comprises 50 convolutional layers with trainable weights. However, these weight layers alone are not sufficient for achieving accurate brain tumor detection. Additionally, the features from the initial layers are not effectively propagated to the lower layers, resulting in inaccurate brain tumor detection. Consequently, modifications have been implemented to the original ResNet50 to address these issues. Notably, an extra convolutional layer has been introduced, leading to an increase in trainable parameters (which are the weights in the convolutional layer). This addition enhances the architecture's ability to effectively capture complex features and patterns in the data, ultimately improving its performance.

Moreover, a technique called depth concatenation has been employed to enhance feature maps in the lower layers of the model. This technique involves stacking feature maps from different layers together. To ensure compatibility for this process, the feature maps are resized before concatenation. By combining information from various layers, the model can extract and utilize a wider range of features, contributing to its effectiveness in handling intricate tasks.

In addition to these structural changes, batch normalization has been integrated to enhance training outcomes. This technique standardizes input for each layer, addressing challenges related to shifts in internal covariates during training. This approach speeds up convergence, improves gradient flow, and facilitates a more stable and efficient training process.

The use of the ReLU activation function is also maintained, effectively introducing non-linearity to the model. This function helps the model capture complex relationships within the data, enabling it to learn and represent intricate features more effectively.

Overall, the careful refinements introduced to the ResNet50 architecture, including the convolutional layer, depth concatenation, and batch normalization, along with the continued use of the ReLU activation function, result in a more capable and versatile model. These adjustments were thoughtfully made to improve the original ResNet50 framework, leading to improvements in performance and feature extraction.

PERFORMANCE COMPARISON

After undergoing training, the proposed model was subjected to a comparative analysis with other deep learning models that were previously documented in existing research papers. The models selected for comparison within this study are AlexNet, GoogleNet, ResNet18, and ResNet50, all of which have been previously employed for brain tumor detection.

To facilitate this comparison, adjustments were made to these models by removing the original fully connected layer and inserting a new one, ensuring alignment with the objectives of this study. Initially designed to classify multiple classes, the models are reconfigured to focus solely on the detection of two classes. This involves the removal of their original final fully connected layers and the subsequent insertion of new fully connected layers tailored to the study's scope. These modified models are subsequently trained using the same dataset that was utilized to train the proposed model.

The results obtained from the training process are then harnessed to facilitate a comprehensive performance comparison. The performance metrics employed for this evaluation encompass accuracy, sensitivity, specificity, and precision. These metrics collectively provide insights into the models' effectiveness in correctly classifying instances of the targeted classes, thereby enabling a meaningful assessment of their relative performance. The equations of the performance metrics can be found in [12].

RESULTS AND DISCUSSIONS

Once the performance metrics for all the deep learning models have been computed, they are employed for the purpose of performance comparison. This process serves to demonstrate the superior performance of the proposed model in contrast to other models utilized for brain tumor detection. The performance metrics, encompassing accuracy, sensitivity, specificity, and precision, for each of these models are comprehensively presented in Table 1.

Table 1. The outcomes derived from diverse deep learning models are assessed on the testing set. The best results are indicated in bold.

Model	Accuracy	Sensitivity	Specificity	Precision
AlexNet	0.9602	0.9182	0.9993	0.9992
GoogleNet	0.8583	0.9104	0.8097	0.8168
ResNet18	0.9699	0.9392	0.9985	0.9983
ResNet50	0.9703	0.9384	**1.0000**	**1.0000**
Proposed Model	**0.9752**	**0.9486**	**1.0000**	**1.0000**

The accuracy metric indicates the overall correctness of the model's predictions. The proposed model achieved the highest accuracy of 0.9752, indicating its proficiency in making accurate predictions compared to other models. Notably, ResNet50 and ResNet18 also demonstrated commendable accuracy levels of 0.9703 and 0.9699, respectively. AlexNet followed closely with an accuracy of 0.9602.

Sensitivity, which measures the model's ability to correctly identify positive instances, was highest for the proposed model (0.9486), signifying its effectiveness in detecting true positives. ResNet18 and ResNet50 also showcased strong sensitivity values of 0.9392 and 0.9384, respectively, underlining their competence in correctly identifying positive cases.

Specificity denotes the model's aptitude for correctly identifying negative instances. The proposed model and ResNet50 achieved perfect specificity scores of 1.0000, showcasing their ability to accurately identify true negatives. AlexNet and ResNet18 also demonstrated noteworthy specificity, achieving scores of 0.9993 and 0.9985, respectively. In contrast, GoogleNet displayed comparatively lower specificity (0.8097), indicating its challenges in correctly identifying negative cases.

Precision, a measure of the model's precision in correctly predicting positive instances, was consistently high across models. ResNet50 and the proposed model achieved precision scores of 1.0000, indicating their precision in identifying true positives. AlexNet, GoogleNet, and ResNet18 also exhibited favorable precision, with values of 0.9992, 0.8168, and 0.9983, respectively.

Apart from performance metrics, the Receiver Operating Characteristic (ROC) curve can also serve as a tool for performance comparison. The ROC curve provides a comprehensive graphical representation indicating the model that performs the best, based on the area under the curve. Figure 4 presents the ROC curves for each model.

According to the ROC curve, the proposed model exhibits the largest area under the curve, indicating its superior accuracy compared to all other models. The second-best performing model is ResNet50, with a slightly smaller area under the curve than the proposed model. Following ResNet50 is ResNet18, succeeded by AlexNet, and finally, GoogleNet demonstrates the smallest area under the curve.

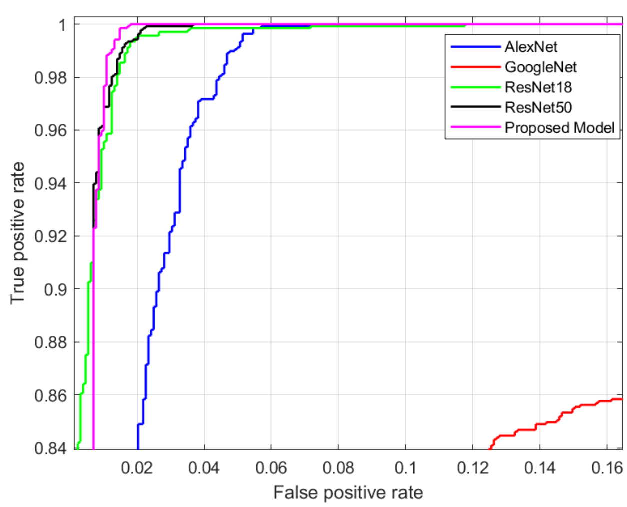


Figure 4. The ROC curve for each model. The proposed model performs the best.

In summary, the proposed model exhibited superior performance across all evaluated metrics, with high accuracy, sensitivity, specificity, and precision values. Furthermore, the ROC curve also indicates the superiority of the proposed model. This highlights its effectiveness in brain tumor detection compared to other established models, making it a promising candidate for further applications in medical image analysis.

CONCLUSIONS

An innovative approach to brain tumor classification was presented in this paper, utilizing a modified ResNet50 architecture. The methodology encompassed data preprocessing, architectural enhancements, and rigorous performance evaluation to achieve robust classification results. Through the incorporation of a convolutional layer, depth concatenation, batch normalization, and the ReLU activation function, the ResNet50 architecture was enhanced to effectively capture intricate features in brain tumor images. The proposed model was thoroughly evaluated and compared against established architectures including AlexNet, GoogleNet, ResNet18, and ResNet50. The results demonstrated the superiority of the proposed model in accurately classifying brain tumor instances, as higher accuracy, sensitivity, specificity, and precision values were observed. The advancement of brain tumor classification techniques and the enhancement of medical image analysis methods were contributed to by this study. As technology continues to evolve and new advancements are made in deep learning and medical imaging, opportunities for exploring further enhancements to the proposed model and additional refinements to the ResNet50 architecture can be pursued, enabling the continuous expansion of machine learning techniques to contribute to improved healthcare outcomes and enhanced patient care.

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