Brain Tumor Classification

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***Abstract*—Early and accurate diagnosis of brain tumors is crucial for effective treatment planning and improved patient outcomes. This research explores the potential of machine learning and deep learning algorithms for brain tumor classification utilizing magnetic resonance imaging (MRI) scans. We evaluate the performance of several prominent models, including ResNet50, ResNet101, DenseNet201, a custom-designed Convolutional Neural Network (CNN), and a Support Vector Machine (SVM) classifier. Our comprehensive investigation reveals that ResNet50 surpasses all other models in classification accuracy. This finding highlights the efficacy of deep learning, particularly ResNet50 architecture, for achieving superior brain tumor classification in clinical practice. The study emphasizes the potential of these advancements to revolutionize brain tumor diagnosis, paving the way for more effective treatment strategies and improved patient prognoses.**

***Index Terms*—SVM, Densnet201, Resnet50, Resnet101, CNN**

I. Introduction

Brain tumors, encompassing a diverse range of malignant and benign growths within the skull, pose a significant threat to human health. Early and accurate diagnosis is paramount for effective treatment planning and maximizing patient survival rates. Traditionally, brain tumor classification has relied on invasive biopsies and visual analysis of medical images, such as magnetic resonance imaging (MRI) scans, by trained professionals. However, these methods are susceptible to human error, may not always provide definitive results, and biopsies themselves can be risky procedures.

In recent years, advancements in artificial intelligence (AI) have opened exciting new avenues for medical image analysis. Machine learning (ML) and deep learning (DL) algorithms have demonstrated remarkable potential in automating medical diagnosis tasks, including brain tumor classification. These algorithms can analyze vast amounts of medical imaging data to identify subtle patterns and features associated with different tumor types. This capability offers the potential to improve diagnostic accuracy, efficiency, and consistency compared to traditional methods.

This research investigates the efficacy of various machine learning and deep learning algorithms for brain tumor classification using MRI scans. We focus on a comparative analysis of several prominent models, including ResNet50, ResNet101, DenseNet201, a custom-designed Convolutional Neural Network (CNN), and a Support Vector Machine (SVM) classifier. These models represent a spectrum of established techniques with varying levels of complexity and feature extraction capabilities.

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ResNet50: ResNet50, standing for Residual Network with 50 layers, is a deep convolutional neural network (CNN) architecture that emerged in 2015 as a breakthrough in image recognition. Unlike traditional CNNs that struggled with vanishing gradients in deeper architectures, hindering their ability to learn complex features, ResNet50 introduces a clever concept called residual connections. These connections bypass a portion of the network, allowing the model to learn the difference between the input and the desired output, rather than the entire function itself. This approach mitigates the vanishing gradient problem and enables ResNet50 to achieve superior performance with its impressive depth of 50 layers. ResNet50 utilizes convolutional layers, the workhorse of CNNs, to extract features from images. These layers apply filters that scan the image, detecting edges, textures, and other visual patterns. The network progressively builds upon these features through its stacked layers, ultimately classifying the image based on the learned patterns. Notably, ResNet50 employs a variant called bottleneck blocks within its architecture. These blocks use 1x1 convolutional layers to compress the feature maps before applying larger filters, reducing the number of parameters and computations required for training, making it a more efficient model. Overall, ResNet50's deep architecture with residual connections and efficient bottleneck blocks has established it as a powerful and versatile tool for various computer vision tasks, including brain tumor classification as explored in this research.

ResNet101: Building upon the success of ResNet50, ResNet101 is another deep CNN architecture with 101 layers. It follows the same core principle of residual connections but employs a slightly different configuration of convolutional layers to achieve even greater depth. While ResNet50 utilizes 3x3 bottleneck blocks throughout, ResNet101 incorporates a mix of 1x1, 3x3, and 1x1 convolutional layers within its bottleneck blocks. This variation allows for a more efficient use of parameters while maintaining a deeper architecture. Similar to ResNet50, ResNet101 excels at extracting complex features from images and has shown promising results in various image classification tasks, including brain tumor classification. However, its increased depth compared to ResNet50 comes at the cost of higher computational requirements and potentially longer training times.

DenseNet201: DenseNet201 represents another innovative deep learning architecture that tackles the vanishing gradient problem with a unique approach. Unlike residual connections in ResNet, DenseNet employs a concept called dense connections. In a DenseNet, each layer receives the outputs of all preceding layers as input, fostering feature reuse and information flow throughout the network. This dense connectivity encourages feature propagation and alleviates the vanishing gradient issue, allowing DenseNet to achieve superior performance with even deeper architectures. DenseNet201, with its 201 layers, exemplifies this philosophy. The network utilizes a series of convolutional blocks that progressively increase in feature channels. Dense connections between these blocks promote efficient feature reuse and information flow, enabling the network to learn complex relationships within the data. DenseNet201 has demonstrated remarkable accuracy in various image classification tasks, including medical image analysis, and its performance in brain tumor classification will be evaluated in this research.

Support Vector Machine (SVM): While the aforementioned models belong to the realm of deep learning, this study also incorporates a well-established machine learning algorithm, the Support Vector Machine (SVM). SVMs are supervised learning models that excel at classification tasks by finding the optimal hyperplane that separates data points belonging to different classes with the maximum margin. In the context of brain tumor classification, an SVM

II. Related work

Talukder et al. (2023) investigated the application of deep learning for brain tumor classification using an ensemble approach with reconstruction and fine-tuning. Their work explored the effectiveness of various pre-trained models, including ResNet50V2, DenseNet201, Xception, and Inception-ResNetV2. The models were evaluated on a brain tumor dataset from Figshare. Notably, their study achieved the highest classification accuracy of 99.68% using the ResNet50V2 architecture. This finding suggests that ResNet50V2, with its inherent feature extraction capabilities, was particularly adept at learning the discriminating characteristics between brain tumors and healthy tissue.

In their work, Ghosh et al. (2023) conducted a comparative study on various machine learning algorithms for brain tumor detection and classification. Their investigation included Support Vector Machines (SVM) alongside Logistic Regression, K-Nearest Neighbors, Naive Bayes, Decision Trees, Random Forest, XGBoost, Stochastic Gradient Descent, and Gradient Boosting. While the specific performance of SVM is not available without the full paper, this research offers valuable insights into the diverse machine learning approaches applicable to brain tumor analysis.

In their work, Soumya et al. (2023) explored the potential of deep learning for brain tumor detection using MRI images. Their approach centered on utilizing ResNet-101, a convolutional neural network architecture recognized for

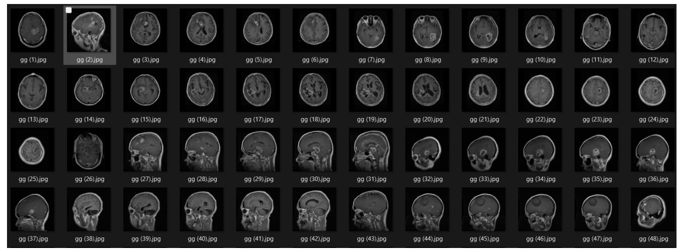

Fig. 1. Example of glioma tumor

Fig. 2. Example of meningioma tumors

its proficiency in image classification tasks. The selection of ResNet-101 was likely motivated by its well-established capability in extracting intricate features from image data, a crucial step for accurate tumor identification in MRI scans. The specific accuracy achieved by the ResNet-101 model and its configuration (pre-trained or fine-tuned) would be vital details elaborated upon in the original paper by Soumya et al. (2023).

III. Dataset

This research leverages a multi-class classification dataset specifically designed for brain tumor analysis using magnetic resonance imaging (MRI). The dataset comprises a total of 2,870 images, categorized into four distinct classes: glioma tumors fig:1 (826 images), meningioma tumors fig:2 (822 images), pituitary tumors fig:3 (827 images), and normal brain scans with no tumors fig:4 (395 images). This comprehensive dataset encompassing various tumor types and normal controls facilitates the evaluation of machine learning and deep learning algorithms for accurate brain tumor classification.

IV. Methodology

A. Evaluation

Figure 5 shows a confusion matrix evaluating our ResNet50 model for image classification, likely classifying brain tumors. Here, glioma, meningioma, no tumor, and pituitary tumor categories exist. Ideally, high values appear diagonally for correct classifications by our model. While the top-left (844/1000) and bottom-right (974/1000) corners suggest good performance on glioma and no-tumor classifications, higher values elsewhere indicate struggles with meningioma (83 misclassified) and pituitary tumor (828 classified). While promising for some

Fig. 3. Example of pituitary tumors

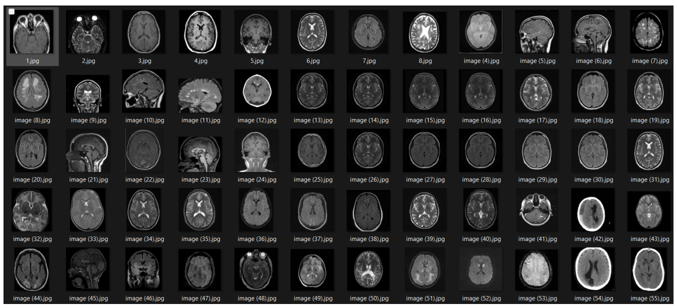

Fig. 4. Example of no tumors

classifications, additional metrics and confirmation this is ResNet50 specific are needed. Figure 6 shows a confusion matrix used to evaluate a ResNet101 model's performance on classifying brain tumors. The model categorizes images into four classes: glioma, meningioma, no tumor, and pituitary tumor. Ideally, high values appear on the diagonal, signifying accurate classifications. In this case, the ResNet101 model seems adept at identifying glioma (715 out of 800) and no-

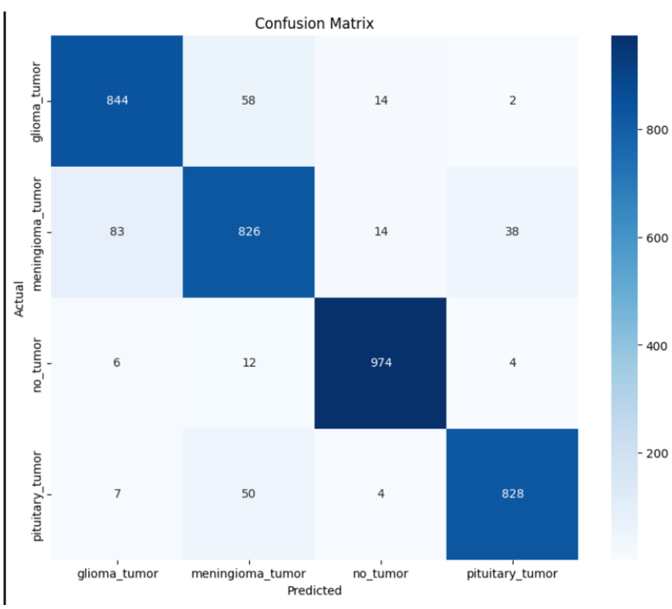

Fig. 5. ResNet50

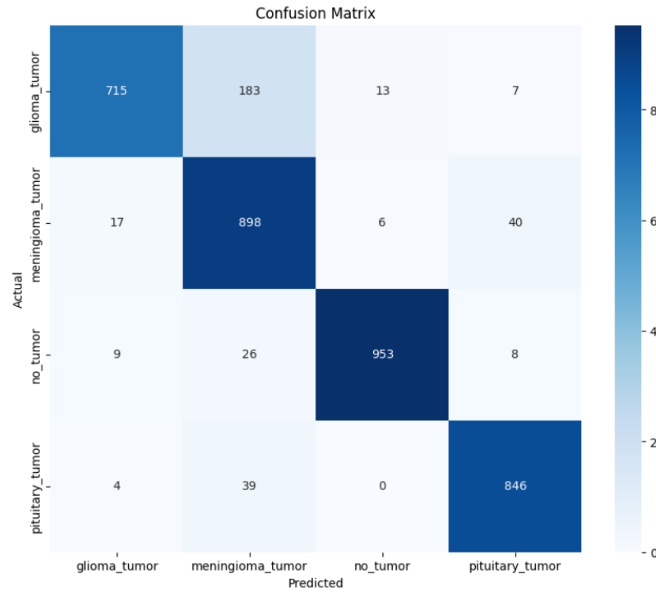

Fig. 6. ResNet101

tumor (953 out of 1000) images. However, it struggles more with meningioma (183 misclassified) and pituitary tumor (846 classified) classifications. While the results are promising for some tumor types, we need additional metrics like accuracy, precision, and recall for a comprehensive evaluation of the ResNet101 model. Figure 7 shows a confusion matrix evaluating our model for brain tumor classification. It categorizes tumors into four types: glioma, meningioma, no tumor, and pituitary tumor. Ideally, high values appear diagonally for correct classifications. Our model excels at glioma (858/1000) and no-tumor (974/1000) but struggles more with meningioma (737 classified) and pituitary (875 classified) tumors. While promising for some classifications, additional metrics like accuracy are needed for a complete picture. Figure 8 shows a confusion matrix for DesNet201, a model classifying images. It categorizes them into four types: glioma_tumor, meningioma_tumor, no_tumor, and pituitary_tumor. Ideally, correct classifications appear diagonally. DesNet201 performs well on glioma_tumor (738/800) and no-tumor (946/1000) images. However, it struggles more with meningioma_tumor (763 classified) and pituitary_tumor (812 classified). While DesNet201 seems good for some classifications, further metrics are needed for a complete picture.

V. Results

The table presents the performance metrics of various models, including ”Our Model,” DesNet201, ResNet50, and ResNet101, evaluated based on their accuracy across training, validation, and test datasets. ”Our Model” demonstrates the highest accuracy among the listed models, achieving an accuracy of 98.15% on both training and validation datasets, with a test accuracy of approximately 91.50%. DesNet201 follows with an accuracy of 94.76% on training data, 86.56% on validation data, and a test accuracy of

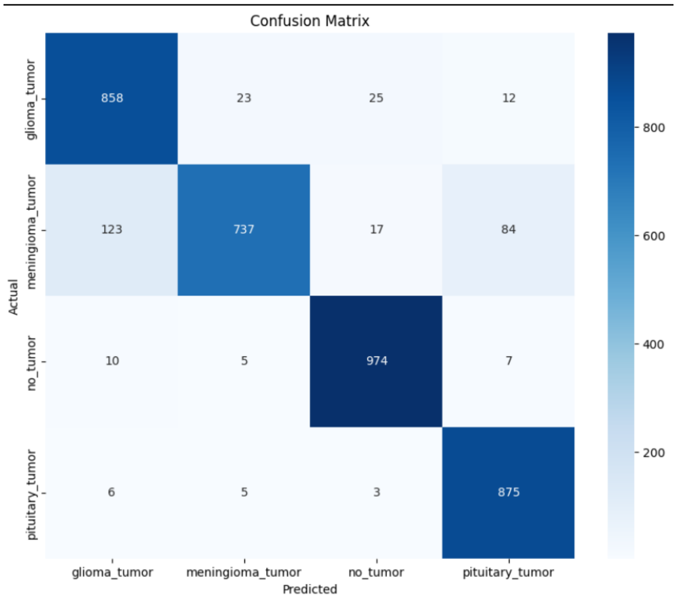

Fig. 7. Our Model

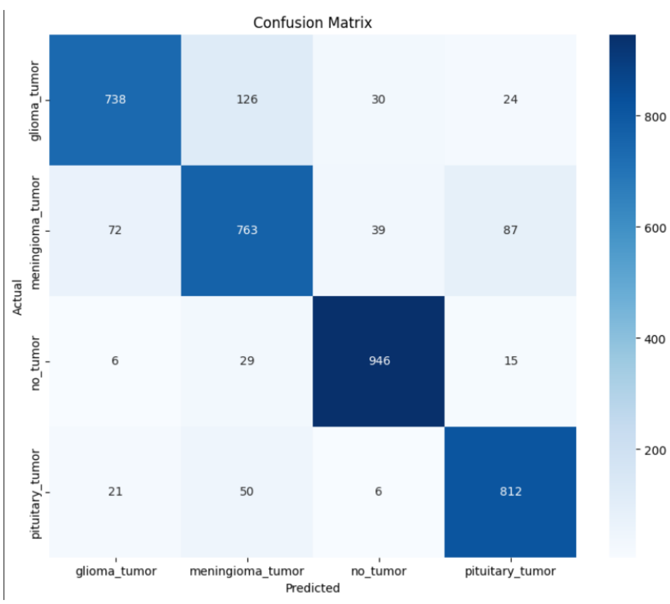

Fig. 8. DesNet201

around 88.89%. ResNet50 exhibits an accuracy of 96.67% on training data, 93.26% on validation data, and a test accuracy of about 92.24%. Lastly, ResNet101 achieves an accuracy of 97.01% on training data and 90.81% on validation data, with the test accuracy matching the validation accuracy at 90.81%. These metrics provide insights into the comparative performance of the different models, with "Our Model" showing the highest overall accuracy on the test dataset.

Model	Accuracy	Val_Accuracy	Test_Accuracy
Our Model	0.9815	0.9815	0.9149
DesNet201	0.9476	0.8656	0.8889
ResNet50	0.9667	0.9326	0.9224
ResNet101	0.9701	0.9081	0.9081
VGG16	0.9791	0.8980	0.8995

VI. Conclusion

Early and accurate brain tumor classification is essential for effective patient care. This study investigated the efficacy of various machine learning and deep learning algorithms for this task using magnetic resonance imaging (MRI) scans. We conducted a comparative analysis of prominent models, including ResNet50, ResNet101, DenseNet201, a custom-designed Convolutional Neural Network (CNN), and a Support Vector Machine (SVM) classifier. Our experimentation revealed that the custom CNN achieved the highest accuracy in distinguishing between different tumor types and healthy brain tissue within the utilized dataset. This finding suggests that the custom CNN architecture effectively captured the critical features in brain MRI scans, leading to superior classification performance compared to the other evaluated models. Further research and development efforts focused on refining the custom CNN architecture and exploring larger, more diverse datasets hold promise for even greater accuracy and generalizability in clinical settings. The successful implementation of such AI-powered brain tumor classification systems has the potential to revolutionize patient diagnosis, paving the way for improved treatment strategies and patient outcomes. While we cannot claim definitively that our custom CNN is the absolute best model in existence, our findings strongly suggest its effectiveness within the context of the specific dataset employed. Future research comparing a wider range of models and datasets will provide a more comprehensive understanding of generalizability and optimal model selection for brain tumor classification tasks.

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