Revolutionizing brain tumor diagnoses: a ResNet18 and focal loss approach to magnetic resonance imaging-based classification in neuro-oncology

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ABSTRACT

Brain tumor diagnosis remains a critical challenge in neuro-oncology, where accurate and timely identification of malignancies can significantly impact patient outcomes. This research explores the integration of deep learning techniques, specifically leveraging the ResNet18 architecture coupled with focal loss, to enhance the classification accuracy of magnetic resonance imaging (MRI)-based brain tumor diagnoses. ResNet18, known for its powerful feature extraction capabilities, was employed to analyze MRI scans, while focal loss was utilized to address class imbalance issues prevalent in medical datasets. The model was trained on a comprehensive dataset, achieving an accuracy of 95.54%. These results demonstrate the potential of this approach in providing robust and precise diagnostic support in clinical settings, potentially revolutionizing the current methodologies in brain tumor detection and classification. The integration of advanced neural networks with specialized loss functions presents a significant advancement in the field, paving the way for more reliable and automated neuro-oncological diagnostics.

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1. INTRODUCTION

Accurately identifying and classifying brain tumors using medical imaging techniques is essential in the field of contemporary healthcare. There are many obstacles in neuro-oncology, and one of the most significant ones is determining the exact location, kind, and course of treatment for brain tumors. Magnetic resonance imaging (MRI) has become an indispensable tool, providing detailed anatomical information essential for diagnosing brain pathologies, including tumors [1]–[5]. The World Health Organization (WHO) states that brain tumors significantly increase cancer-related mortality and morbidity rates [6]. Thus, the importance of early and accurate diagnosis cannot be overstated, especially in light of the rising global incidence of these diseases. Prompt intervention and improved patient outcomes can only be achieved with timely and accurate diagnosis [7]–[9]. The fields of medical imaging and artificial intelligence (AI) have advanced significantly in recent years, particularly with the introduction of convolutional neural networks

(CNNs). These deep learning architectures have revolutionized the field by demonstrating hitherto unseen abilities in image analysis, pattern recognition, and feature extraction. CNNs are especially promising for medical image analysis applications since they automatically learn complicated hierarchical representations from raw data, which makes them useful for tasks like brain tumor diagnosis and classification [10]–[14]. Using CNNs in medical imaging has several advantages, especially when it comes to identifying brain cancers from MRI images. CNNs are very skilled in recognizing complex spatial connections in pictures, which facilitates the identification of minuscule variations and patterns that may be indicative of illness. Due to their ability to manage massive datasets while retaining high accuracy and resilience, CNNs have progressed to the forefront of medical image processing, enabling more precise and effective diagnoses [14]–[17].

Additionally, because of their novel residual learning framework, residual networks (ResNets) have become a well-known paradigm within the spectrum of CNN architectures. ResNets introduce skip connections that facilitate residual mapping learning, hence addressing training issues with very deep neural networks. This architecture not only reduces problems associated with vanishing gradients and speeds up convergence during training, but it also improves model performance [18]–[23]. This study investigates the classification of brain cancers from MRI scans using CNNs, with a focus on the ResNet architecture. Through rigorous testing and analysis, the goal is to demonstrate the efficacy and advantages of applying these state-of-the-art neural network models for the precise and automated diagnosis of brain cancers. This contribution aims to further the field of neuro-oncology and enhance patient care. Many academics' contributions to the categorization of brain tumors have been extremely beneficial. In order to increase accuracy, A neural network technique based on unsupervised learning was presented by Goswami and Bhaiya [24]. for the classification of magnetic resonance images of the human brain. They separate the process of diagnosing brain tumors into several stages in their work. This approach shows promise based on classification findings for various disorders on a range of MR images. A unique multi-stage automatic technique for brain tumor diagnosis and neo vasculature assessment was proposed by Szwarc *et al.* [25]. The outcomes of independently carried out hand delineations and contrast-enhanced lesions detection have been compared. A modified U-Net structure based on residual networks that employ sub-pixel convolution at the decoder portion and periodic shuffling at the encoder section of the original U-Net was also proposed by Pedada *et al.* [26]. This strategy appears difficult, and the outcomes are not very appealing.

The method input proposed by Thara and Jasmine [27] after pre-processing the image, the K means and fuzzy C means clustering techniques are used to segment the image. A successful modified area growing technique for brain tumor detection was proposed by Kavitha *et al.* [28]. In addition to the normal intensity constraint, modified region growth imposes an orientation constraint.

2. METHOD

2.1. Dataset and preprocessing

Our dataset, which is used in this study, consists of MRI images that have been methodically classified into two main groups: "Tumor" and "No Tumor." There is now even more specificity in the "Tumor" class thanks to the distinction between Glioma and Meningioma. Gliomas, which are produced from glial cells, can arise in different sections of the brain, but meningiomas start in the meninges, the protective membranes that wrap the brain and spinal cord. The size of the dataset is considerable because it contains 4,255 images that have been selected for training. Out of these, 2,660 images belong to the tumor class (which includes Meningioma and Glioma), whereas the remaining 1,595 images do not exhibit any tumor involvement. A specific group of 1,011 photos has been reserved for testing in order to assess the model's performance. This subset consists of 405 images showing situations where "No Tumor" is detected and 606 images combining meningioma and glioma tumor classes.

To provide a visual representation of our dataset, Figure 1 depicts an illustrative example. The MRI images were carefully processed through a number of preprocessing stages before CNN models were trained. The principal aim of these preprocessing methods was to improve the models' capability for feature extraction and to enable a wider degree of generalization. The first step was to uniformly apply a blurring filter to each image. Reducing image noise would improve overall image quality, which was the aim of this filtering process. In doing so, the impact of unimportant artifacts included in the original MRI images was reduced, enhancing the CNN models' capacity to identify significant features. In addition to blurring, some images were treated to a controlled rotation. Two purposes were fulfilled by this rotational augmentation: it improved the dataset's robustness and added to its diversity. Better generalization was encouraged by controlled rotations that exposed the models to various viewpoints and orientations of brain areas. Figure 2 demonstrates the effect of preprocessing. In order to provide a more comprehensive and varied dataset, a purposeful mix of rotation and blurring methods was applied. CNN models were able to differentiate between tumor and non-neoplastic entities on a variety of MRI images with the use of this extended dataset, which comprised a wide range of attributes and views. Ultimately, the objective of this preprocessing technique was to optimize the models' robustness and accurate classification in real-world scenarios.

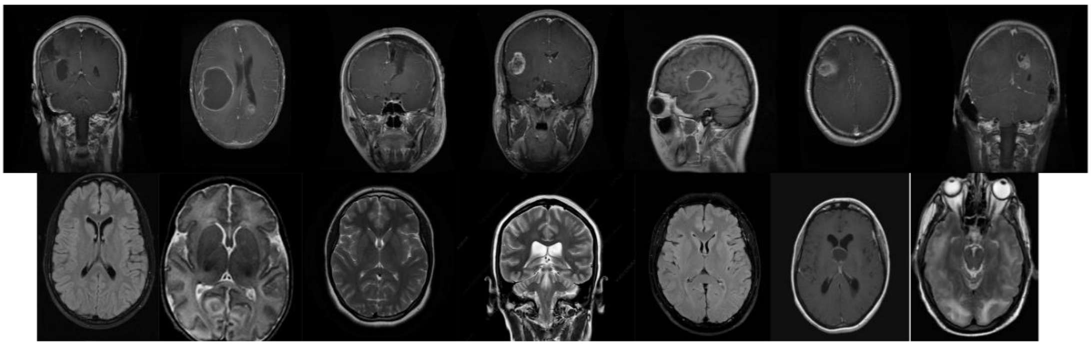

Figure 1. The 1st row consists of images belonging to 'Tumor' class and the 2nd row consists of images belonging to 'No Tumor' class

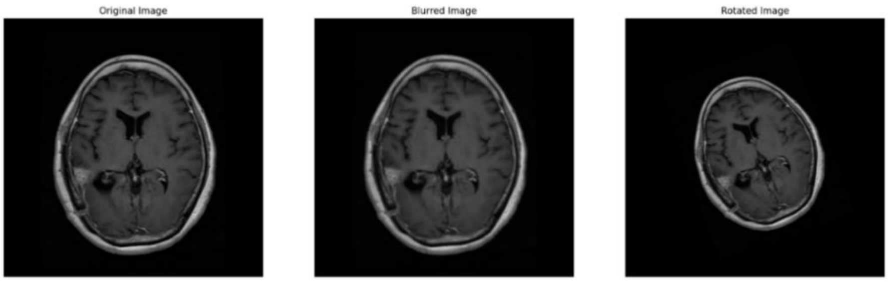

Figure 2. The original image, blurred image, and controlled rotation of the blurred image

2.2. Approach

The ResNet architecture has played a pivotal role in augmenting the capabilities of deep neural networks across an array of computer vision challenges and has found widespread use in medical image processing. One of the most significant advances made possible by ResNet is the concept of residual learning, which offers a fresh solution to issues such as the vanishing gradient problem and promotes faster convergence during training. The residual block, a key building block, lies at the center of the ResNet design. The key element of this block is the introduction of "skip connections" or "identity shortcut connections," which are unique in that they allow the network to learn residual mappings.

2.2.1. Identity mapping

In traditional neural networks, layers learn to approximate the desired mapping. However, ResNet takes a unique approach by focusing on identity mapping. Instead of learning the entire desired mapping, the network concentrates on learning residuals-the difference between the desired mapping and the actual output of a layer.

2.2.2. Shortcut connection

The incorporation of a shortcut connection is a key element of the residual block. This connection strategically bypasses one or more layers by adding the input of a layer to its output, establishing a direct "shortcut" path. This shortcut facilitates the preservation of the original information (identity) alongside the learned residuals. In practical terms, if the network determines that the optimal transformation is in proximity to the identity, it can efficiently adjust the weights of the residual part to zero, streamlining the training process.

Essentially, the ResNet architecture solves training problems for deep neural networks and improves the network's capacity to extract complex features and representations. It does this by utilizing an inventive residual learning framework and identity shortcut connections. This flexibility is especially helpful when analyzing medical images, as accuracy and productivity are critical.

2.3. ResNet18 architecture

The composition of ResNet18's neural network design, which does not include the pooling and fully connected layers, is eighteen layers. Each stacked residual block in the design has two convolutional layers, batch normalization, ReLU activation functions, and a skip connection. The architecture is built around these blocks.

2.3.1. Initial layers

The design starts with a 7×7 convolutional layer with a stride of 2, which makes it easier to downsample the input picture. Next, a max-pooling layer is used to enhance the representation even further. Together these layers streamline the processing of the data for more efficient analysis.

2.3.2. Residual blocks

There are four groups of residual blocks in ResNet18. Every group consists of many leftover blocks, adding up to the architecture's total of eighteen levels. Remaining blocks play a crucial role in identifying and extracting intricate information from the incoming data.

2.3.3. Final layers

A global average pooling layer, one of the terminal layers of ResNet18, calculates the output's average throughout its spatial dimensions. After that, a fully linked layer that uses SoftMax activation is used to categorize data into several classifications. By using the characteristics, it has gleaned and learnt across its layers, this last step guarantees the network's ability to generate insightful predictions. In Figure 3, the ResNet18 architecture is visually represented, showcasing the sequential arrangement of its components. This architecture's design, characterized by residual blocks and skip connections, enables effective feature extraction, gradient flow, and classification, making it well-suited for a variety of tasks, including image classification.

Focal loss was used to rectify the underlying class disparity in this implementation between the 'Tumor' and 'No Tumor' categories. In situations when there is class imbalance, the traditional cross-entropy loss function tends to be skewed in favor of the majority class, creating what is known as the "class imbalance problem." This problem is addressed by focal loss, which selectively lowers weights the loss attributed to correctly categorized samples and emphasizes difficult-to-classify cases. Focal loss introduces a modulating factor that diminishes the contribution of easily classified examples to the overall loss, while concurrently accentuating the loss for more difficult, misclassified examples. An essential feature of focal loss is the inclusion of a tunable focusing parameter (γ) that governs the rate at which the loss for well-classified examples is diminished. Adjusting γ allows for a tailored balance, with lower values intensifying the down-weighting effect on easily classified examples and focusing the model's attention on correctly classifying intricate instances.

When implementing ResNet18 for classification tasks involving imbalanced classes, focal loss is integrated as the custom loss function during training. This strategic integration ensures that the model prioritizes learning from the minority class, thereby improving its discernment and classification of rare or challenging examples. Throughout the training phase, focal loss replaces the standard cross-entropy loss function, calculating the loss for each instance in the mini-batch and subsequently averaging to obtain the overall loss. The hyperparameter γ in focal loss can be fine-tuned through empirical experimentation to achieve the desired equilibrium between accentuating challenging examples and diminishing the influence of well-classified ones.

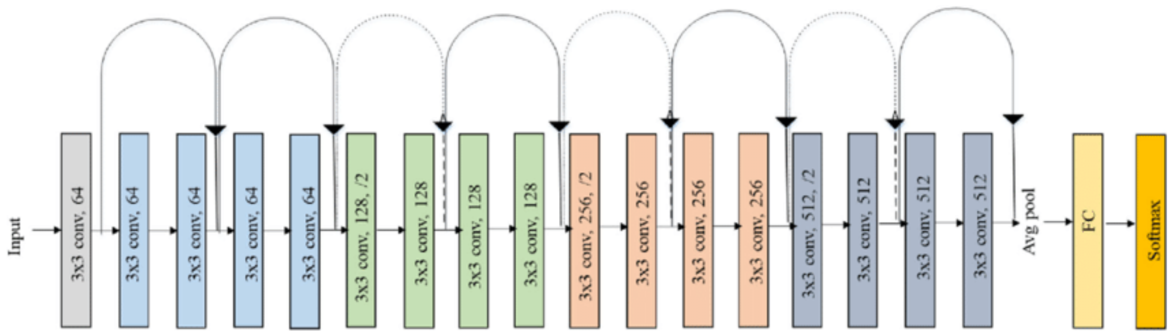

Figure 3. ResNet18 architecture

By incorporating focal loss with ResNet18, the training process of the model is optimized to effectively handle imbalanced classes. This enhancement enhances the model's proficiency in classifying MRI images as either tumor or non-tumor, particularly in situations where a significant class imbalance is present in the dataset. Refer to Figure 4 for a visual representation of the proposed architecture. The model was trained using the AdamW optimizer and minimizing the focal loss function over a period of 25 epochs. The parameters of the model were iteratively refined over the chosen epochs in order to maximize its performance in correctly categorizing brain MRI images. Improving the model's capacity to discriminate between tumor and non-tumor classes was the main goal of this training.

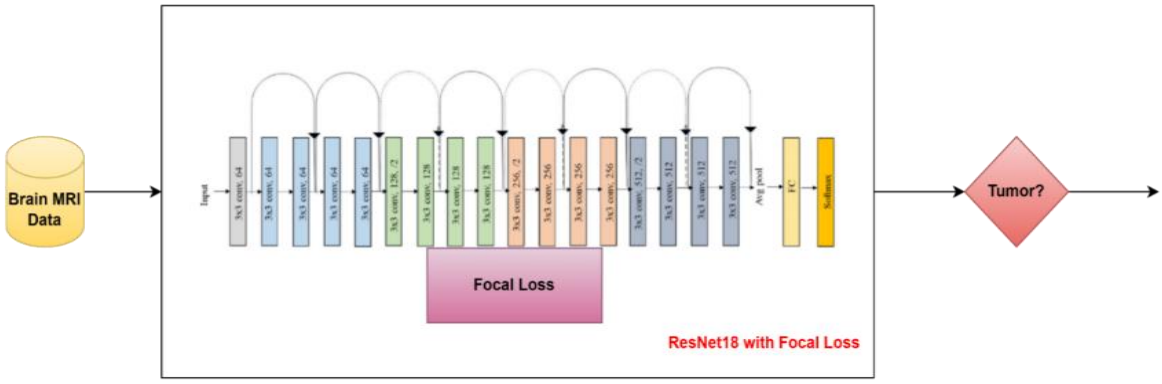

Figure 4. Proposed ResNet18 with focal loss model architecture

3. RESULTS AND DISCUSSION

The training and validation loss profiles are presented in Figure 5, where a unique pattern resembling the famous L curve indicates the model's convergence throughout training. This pattern demonstrates the repeated refinement of the model's parameters, which continuously reduces losses over the course of the epochs. Excellent performance metrics were shown by the model after 25 epochs. The model's ability to correctly classify brain MRI pictures within the training dataset was demonstrated by the training accuracy of 96.5%. Concurrently, a significant 92.25% validation accuracy was attained, highlighting the model's strong generalization skills on untested data and confirming its effectiveness outside of training samples.

The area under the curve (AUC) metric throughout the course of 25 epochs is visualized and shown in Figure 6. An important parameter for assessing the model's ability to distinguish between tumor and non-tumor groups is its area of overlap (AUC). The model's learning trajectory, or the AUC curve, shows how the model's capacity to distinguish between classes has changed over the course of the training epochs. The increasing trend in the AUC curve highlights the model's improved ability to distinguish between tumor and non-tumor cases and supports the model's better discriminatory performance during the training phase.

The performance on the test data set that consists of 1011 images, the model achieved an accuracy of 95.54%. The model has a sensitivity of 96%, which emphasizes the ability of the model to correctly identify tumors. The model achieved a specificity of 95%, maintaining a good balance between correctly determining and tumors and reducing the number of false positives. The confusion matrix is depicted in Figure 7 which emphasizes the performance of the model. The false negatives, where the model has not correctly determined the presence of a tumor is low at 26. False Positives, where the model has wrongly detected the presence of a tumor is also low at 19. All of the data together highlight how well the model extracts complex information from MRI scans, leading to high accuracy rates and a noticeable increase in discriminating ability, as the AUC analysis and the confusion matrix show. Its ability to achieve high accuracy of 95.54% and distinguish between tumor and non-tumor classifications validates the model's potential use in clinical settings, especially for accurate brain tumor classification. The analysis of the CNN model with ResNet18 architecture for the purpose of classifying brain tumors from MRI images has encouraging implications for the fields of neuro-oncology and medical imaging. The model's convergence during training is highlighted by the L curve pattern in Figure 5, which is a visual depiction of loss curves. This convergence indicates that the model's weights and parameters have been refined iteratively, leading to decreasing losses and demonstrating the model's ability to extract discriminative features from MRI images. The model's significant capacity to discriminate between tumor and non-tumor classes is demonstrated by the remarkable accuracy of 95.54%.

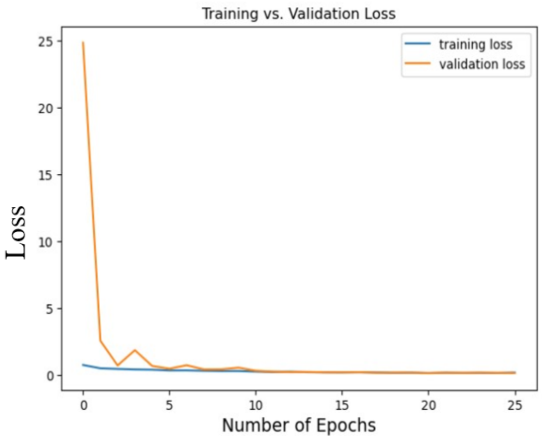

Figure 5. Training and validation loss curves

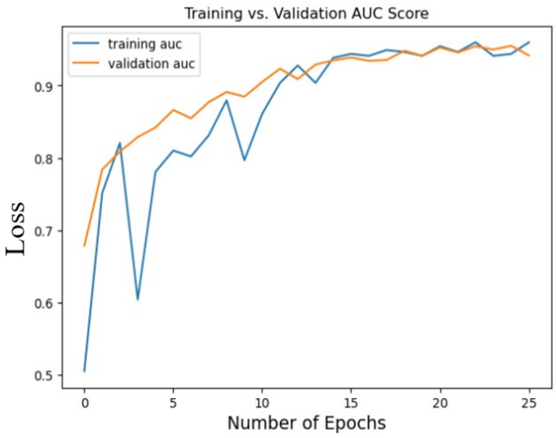

Figure 6. AUC progression on training and validation data

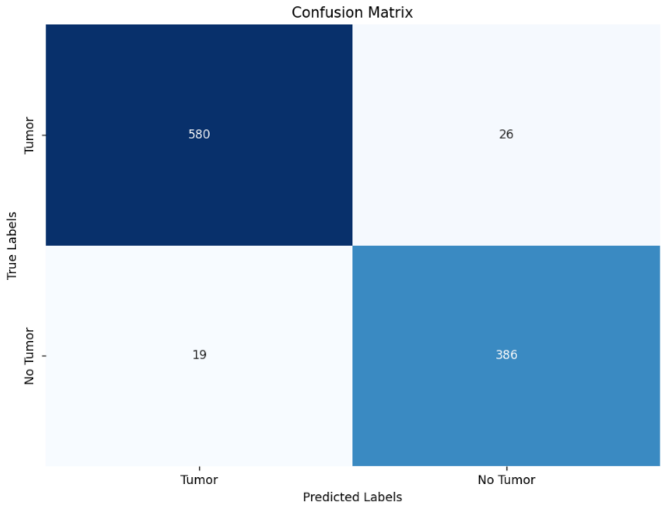

Figure 7. Confusion matrix

The high training accuracy demonstrates how well the model can identify complex patterns. Its clinical utility is confirmed by the high specificity, highlights the model's strong generalization ability. The excellent discriminating ability and high accuracy rates will have a significant influence on clinical applications. When a model can effectively categorize MRI images of brain tumors, clinicians may find it valuable in making faster and more accurate patient diagnoses. This capability might make it possible to create treatment programs tailored to each patient and to intervene promptly. Given the performance of the supplied model, it is imperative to acknowledge its limitations. Despite the size of the dataset, it may still be enhanced to increase the model's ability to generalize across various patient demographics and imaging variations.

4. CONCLUSION

The integration of ResNet18 with focal loss for MRI-based brain tumor classification demonstrates a significant advancement in neuro-oncological diagnostics. Our model achieved a training accuracy of 96.5% and a validation accuracy of 92.25%, indicating robust performance. Further evaluation on a test set of 1011 images, consisting of 405 "No Tumor" and 606 "Tumor" cases, revealed a sensitivity of 96% and a specificity of 95%. The confusion matrix analysis showed that the model correctly classified 580 out of 606 tumor images and 386 out of 405 no tumor images, underscoring its high precision and reliability. These results highlight the model's potential in accurately distinguishing between tumor and non-tumor cases, which is crucial for early detection and treatment planning. The high sensitivity ensures that the majority of tumor cases are identified correctly, minimizing the risk of missing malignancies, while the high specificity reduces the likelihood of false positives, thus preventing unnecessary interventions. The use of focal loss addresses the issue of class imbalance which is highlighted by the minimal difference in sensitivity and specificity of the model.

In conclusion, the use of ResNet18 with focal loss represents a promising approach for improving the accuracy and reliability of brain tumor diagnoses from MRI scans. This method offers a substantial contribution to the field of medical imaging and neuro-oncology, paving the way for more efficient and automated diagnostic tools. Future work will focus on expanding the dataset, refining the model, and integrating it into clinical workflows to further validate and enhance its applicability in real-world settings.

Future work will focus on several key areas to build on these promising results. Firstly, we plan to expand the dataset to include a wider variety of tumor types and stages, which will help to improve the model's generalizability and robustness. Secondly, we aim to incorporate additional imaging modalities, such as CT scans and PET scans, to provide a more comprehensive diagnostic tool. Thirdly, integrating the model into a user-friendly clinical decision support system will be prioritized to facilitate its adoption in healthcare settings. Finally, prospective clinical trials will be conducted to validate the model's performance in real-world scenarios, ensuring its efficacy and reliability in actual clinical practice.

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