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Deep Learning-Based Brain Tumor Classification Using Convolutional Neural Network

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Abstract

An essential noninvasive medical diagnostic technique is magnetic resonance imaging (MRI), which is particularly useful for identifying brain cancers. While earlier algorithms proved effective on smaller MRI datasets, their performance suffered on bigger datasets. This study addresses the need for a swift and reliable brain tumor classification system capable of sustaining optimal performance across comprehensive MRI datasets. The convolutional neural network is implemented using the Keras library, incorporating the ResNet50 architecture as a pre-trained model. The ResNet50 model is fine-tuned for the specific brain tumor classification task, with a Global Average Pooling layer, dropout, and a final dense layer with softmax activation. Data augmentation techniques are employed to enhance the model's robustness, including rotation, width and height shifts, and horizontal flips. The training process involves optimizing the model using the Adam optimizer with a learning rate of 0.0001. Early stopping, learning rate reduction on plateau, and model checkpointing are implemented as callbacks to ensure efficient training and prevent overfitting. The proposed model achieves a remarkable accuracy of 99.47 percent after 15 epochs. The classification task involves distinguishing among four classes: glioma, meningioma, pituitary, and no tumor.

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Abstrak

Magnetic Resonance Imaging (MRI) merupakan salah satu teknik diagnostik medis non-invasif yang sangat penting, terutama dalam mendeteksi kanker otak. Meskipun berbagai algoritma sebelumnya telah menunjukkan performa yang baik pada dataset MRI berukuran kecil, efektivitasnya cenderung menurun saat diterapkan pada dataset yang lebih besar. Penelitian ini merespons kebutuhan akan sistem klasifikasi tumor otak yang cepat dan andal, serta mampu mempertahankan performa optimal pada dataset MRI yang lebih kompleks. Model jaringan saraf konvolusional dikembangkan menggunakan pustaka Keras, dengan memanfaatkan arsitektur ResNet50 sebagai model pralatih. Model ini disesuaikan secara khusus untuk klasifikasi tumor otak melalui penambahan lapisan Global Average Pooling, dropout, dan lapisan dense akhir dengan aktivasi softmax. Untuk meningkatkan ketahanan model, digunakan teknik augmentasi data seperti rotasi, pergeseran lebar dan tinggi, serta pembalikan horizontal. Proses pelatihan dilakukan menggunakan optimizer Adam dengan laju pembelajaran sebesar 0,0001. Beberapa callback seperti early stopping, learning rate reduction on plateau, dan model checkpointing turut diterapkan guna memastikan proses pelatihan yang efisien dan menghindari overfitting. Model yang diusulkan berhasil mencapai akurasi sebesar 99,47% hanya dalam 15 epoch. Tugas klasifikasi ini mencakup empat kategori, yaitu glioma, meningioma, tumor hipofisis, dan kondisi tanpa tumor.

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1. INTRODUCTION

Medical imaging, particularly through Magnetic Resonance Imaging (MRI), has ushered in a new era of noninvasive diagnostic capabilities for a range of disorders affecting the brain. However, the sheer volume and intricacy of MRI datasets present challenges in achieving efficient and accurate classification of brain diseases. This paper seeks to make a substantial contribution to this evolving field by proposing a robust machine learning-based approach for the precise classification of brain diseases using MRI images. The inspiration for this research is drawn from the observation that existing systems, though performing admirably on smaller MRI datasets, experience a decline in performance when confronted with larger datasets [1]. The primary objective is to develop a classification system that not only guarantees swift and reliable results but also maintains peak performance across extensive MRI datasets.

Our proposed approach integrates innovative techniques from the fusion of image enhancement, feature extraction, and machine learning methodologies. In the quest for enhancing MRI images, global histogram equalization (GHE) is harnessed to eliminate extraneous details and enhance overall image quality [2]. Following this enhancement, a feature extraction method based on symlet wavelet transform is introduced to derive discriminative features crucial for accurate classification. The choice of the symlet wavelet is pivotal, as its ability to accommodate orthogonal, biorthogonal, and reverse biorthogonal features of grayscale images results in superior classification outcomes [3].

In parallel, we draw insights from recent research. Kang et al. introduced an ensemble approach leveraging deep features from pre-trained convolutional neural networks for brain tumor classification. The ensemble, comprised of features from DenseNet-169, Inception V3, and ResNeXt-50, demonstrated significant improvements, particularly for large datasets. Additionally, Abdalla et al. explored the impact of image augmentation techniques on MRI patient images for brain tumor detection using transfer learning networks. Their results indicated substantial accuracy enhancements, with InceptionV3 achieving a remarkable accuracy rate of 98.44% after employing image augmentation techniques [4]. Inspired by these advancements, our study incorporates an ensemble approach with deep features and image augmentation techniques to bolster the capabilities of our machine learning-based brain disease classification system.

This project aims to develop a machine learning-based brain tumor detection system, with the focus on the use of Convolutional Neural Networks (CNN). The system is designed to proficiently classify brain MRI images into four categories: glioma, meningioma, no tumor, and pituitary. By amalgamating methodologies from image enhancement, feature extraction, and ensemble learning, we strive to advance the accuracy and reliability of brain disease classification, laying the groundwork for an efficient and effective diagnostic tool. The subsequent sections will delve into the details of our proposed approach, encompassing the stages of image enhancement, feature extraction, and classification. This comprehensive undertaking not only aspires to contribute to the ongoing discourse in the field but also seeks to address the imperative need for accurate and swift brain disease identification through the fusion of diverse methodologies and insights gleaned from multiple research endeavors.

2. LITERATURE REVIEW

Radiologists face a difficult problem when it comes to classifying diverse and life-threatening brain tumors. A method of multi-level feature extraction and concatenation is proposed for early brain tumor identification using computer-aided diagnosis tools and pre-trained deep learning models. For brain tumor identification and classification, two pre-trained deep learning models, Inception-v3 and DensNet201, are used and assessed in two different scenarios. In the first scenario, characteristics from several Inception modules are retrieved and concatenated from the pre-trained Inception-v3 model for brain tumor classification. These characteristics are then fed into a softmax classifier. The pre-trained DensNet201 is used in the second scenario to extract features from multiple DensNet blocks, which are concatenated and fed to a softmax classifier for brain tumor classification. A publicly available three-class brain tumor dataset is used to examine these situations. On testing samples, the proposed technique obtains 99.34 percent and 99.51 percent testing accuracies with Inception-v3 and DensNet201, respectively, exhibiting improved performance in brain tumor detection. The results show that the suggested method for brain tumor classification outperforms existing state-of-the-art deep learning and machine learning methods based on feature concatenation utilizing pre-trained models. The use of deep learning models for brain tumor diagnosis, with a focus on the effectiveness of the ensemble method based on dense block concatenation utilizing the DensNet201 pre-trained model. The proposed method has the highest performance in brain tumor identification, with a testing accuracy of 99.51 percent [5].

Brain tumor segmentation (BTS) in magnetic resonance imaging (MRI) is crucial for diagnostic, management, and research purposes. Despite the success of BraTS challenges and developments in CNN and Transformer algorithms, present BTS models frequently overlook the sensible merging of multimodality images.

A clinical knowledge-driven brain tumor segmentation model (CKD-TransBTS) was introduced, which harnesses radiologists' clinical knowledge in diagnosing brain tumors from several MRI modalities. Rather than concatenating all input modalities, restructure them into two categories based on MRI imaging principles. To extract multi-modality image features, a dual-branch hybrid encoder with a Modality-Correlated Cross-Attention (MCCA) block is used. The model combines Transformer and CNN strengths, with an emphasis on local feature representation for precise lesion boundaries and long-range feature extraction for 3D volumetric pictures. A Trans and CNN Feature Calibration (TCFC) block is proposed in the decoder to bridge the gap between Transformer and CNN features. On the BraTS 2021 challenge dataset, the proposed CKD-TransBTS model is compared to six CNN-based and six transformer-based solutions. In terms of brain tumor segmentation, the proposed model outperforms the competition. It is critical to incorporate clinical information into model creation for more effective representation and learning of intrinsic data features beyond labels. The MCCA and TCFC blocks, for example, are emphasized for their usefulness in enhancing segmentation results [6].

Güler and Namlı developed a state-of-the-art CNN-based system on the Nickparvar dataset that employs multiple architectures and rigorous optimization. In their approach, four different CNN models (VGG, ResNet, DenseNet, SqueezeNet) were trained on the full dataset (≈7022 MRI images) and used as feature extractors. The extracted features were then classified using various machine learning algorithms and an ensemble (voting) strategy, along with extensive hyperparameter tuning of the classifiers. Notably, their optimized ResNet-based model attained a 100% accuracy on the 40% test split of the dataset – an unprecedented perfect classification result on this MRI dataset. This was achieved by parameter optimization on the ResNet model, and it underscores the effectiveness of combining deep CNN features with optimized classifiers. (By comparison, their initial experiments without optimization saw lower accuracies – e.g. around 85% using DenseNet+SVM – but the fine-tuning and ensemble methods ultimately yielded near-perfect performance.) Such results illustrate the potential of ensemble and optimization techniques in pushing the accuracy boundaries for brain tumor MRI classification [7].

This study proposes a brain tumor classification method using an ensemble of deep features and machine learning classifiers. In the proposed framework, the concept of transfer learning is adopted, employing several pre-trained convolutional neural networks to extract deep features from brain magnetic resonance (MR) images. The extracted deep features are evaluated by multiple machine learning classifiers, and the top three performing features are selected and combined as an ensemble. This ensemble is then input into several machine learning classifiers to predict the final output. Experiments using three brain MRI datasets demonstrate that the ensemble of deep features significantly improves performance, with support vector machine (SVM) using radial basis function (RBF) kernel outperforming other classifiers, especially for large datasets. On the other hand, another study emphasizes the importance of data augmentation in training transfer learning networks for brain tumor identification. Utilizing augmentation methods on networks such as InceptionV3, VGG16, and DenseNet169, the research found a substantial increase in accuracy. For instance, VGG16 improved from 77.33 percent to 96.88 percent, InceptionV3 from 86.66 percent to 98.44 percent, and DenseNet169 from 85.33 percent to 96.88 percent. Data augmentation proves crucial in enhancing model generalization, particularly when dealing with limited datasets in the context of cancer research [1-2].

3. METHODOLOGY

In the realm of medical image analysis, Convolutional Neural Networks (CNNs) stand as a cornerstone. Originally inspired by the visual processes of the human brain, CNNs excel at capturing intricate spatial hierarchies within images, making them well-suited for tasks like brain tumor classification. Among the repertoire of CNNs, ResNet50 (Residual Network with 50 layers) has emerged as a potent architecture. Introduced by He et al., ResNet50 is particularly renowned for addressing the challenge of vanishing gradients during training, allowing for the successful training of deeper networks [8]. Leveraging the strengths of ResNet50 in our methodology enhances the depth and feature extraction capabilities of our model.

For the practical implementation of these neural networks, we turn to Keras, a high-level deep learning library. Keras provides a user-friendly interface, enabling efficient experimentation with neural network architectures. It serves as the backbone for our model development, ensuring a seamless integration of diverse components. TensorFlow, an open-source machine learning library, complements Keras as the underlying engine. Developed by the Google Brain team, TensorFlow facilitates the deployment and

training of deep learning models. The synergy between Keras and TensorFlow empowers our methodology with the computational robustness required for complex medical image analysis tasks [9]. These foundational elements collectively form the backbone of our proposed method. By strategically integrating CNNs, ResNet50, Keras, and TensorFlow, we lay the groundwork for a sophisticated approach to brain tumor classification, drawing insights from the advancements in deep learning showcased in the referenced literature [3,8,9].

Deep Feature Extraction with CNN-The proposed method leverages the capabilities of Convolutional Neural Networks (CNNs) to extract robust features from brain MRI images. Taking inspiration from the work of Mahalakshmi and Sumathi, a standalone CNN model is integrated into the classification pipeline. This model excels at capturing intricate features, enhancing the discriminative power of the classification process. Effective Data Augmentation for Improved GeneralizationTo address the challenge of limited data and reduce the risk of overfitting, the proposed method incorporates image augmentation techniques. Following the insights of Abdalla et al. [2], rotation, width shift, height shift, and horizontal flip are applied during the training phase. This augmentation introduces variations into the training dataset, enabling the model to generalize more effectively to diverse scenarios and improve overall performance. Advanced Techniques for Enhanced Discrimination-The methodology incorporates advanced techniques to further improve feature discrimination and classification accuracy. Taking inspiration from Siddiqi et al. [10], techniques such as global histogram equalization and symlet wavelet transform are employed to refine the features extracted by the model. These advanced techniques contribute to a more nuanced and discriminative representation of the input data.

This research utilizes the Brain Tumor MRI Dataset by Masoud Nickparvar, comprising 7,023 T1-weight contrast-enhanced MRI images classified into four categories: glioma tumor (1,621 images), meningioma tumor (1,645 images), pituitary tumor (1,757 images), and no tumor (2,000 images). The dataset, totaling approximately 156 MB in JPEG format, consists of images with varying high spatial resolutions (512×512 and 256×256 pixels), which were uniformly resized during preprocessing for consistency. Data are structured into training (5,712 images: 1,595 no tumor, 1,321 glioma, 1,339 meningioma, 1,457 pituitary) and testing sets (1,311 images: 405 no tumor, 300 glioma, 306 meningioma, 300 pituitary), arranged in hierarchical folders provided by Kaggle. Nickparvar compiled the dataset from multiple public sources, including Figshare and other Kaggle contributions, and it is released under the CC0 Public Domain license, allowing unrestricted use and distribution.

In summary, our proposed method focuses on leveraging standalone CNN models, effective data augmentation, and advanced feature extraction techniques to create a comprehensive approach for brain tumor classification. Each component is carefully selected and integrated to enhance the overall performance of the model in capturing relevant patterns from MRI images.

4. RESULT AND DISCUSSION

The experimental process begins with the preparation and preprocessing of a diverse brain tumor MRI dataset, comprising four classes. Images are standardized, resized, and filtered to reduce noise, followed by division into training and testing sets. Data augmentation techniques, including rotation and flip, are employed to augment the training dataset, enhancing the model's ability to generalize. The proposed model architecture utilizes the ResNet50 convolutional neural network as a feature extractor, with subsequent layers for regularization and classification. Training is conducted over 15 epochs with callbacks for early stopping and model checkpointing. Evaluation on the testing set yields classification metrics, and the model's learning progression is visualized through training history plots. Lastly, a sample image is used for prediction, showcasing the model's capability to accurately classify brain tumor types.

In our proposed brain tumor classification method, weemploy a designed hierarchical architecture to successfully evaluate brain MRI images. This involves extracting images from a carefully selected dataset containing four primary tumor classes: glioma, meningioma, non-tumor, and pituitary. The dataset is methodically divided into training and testing sets, ensuring a fair representation of various tumor types in both subsets. Subsequently, the retrieved brain MRI images undergo a series of preprocessing processes aimed at improving image quality and adjusting visual characteristics. Each step in this process is carried out methodically to maintain information integrity and visual representation consistency for each tumor class. Our brain tumor classification algorithm is then trained and evaluated using properly prepared datasets. The combination of a structured architectural framework and rigorous image preprocessing is predicted to enhance the model's ability to distinguish between different forms of brain cancer, contributing significantly to precision and diagnostic reliability in key healthcare activities.

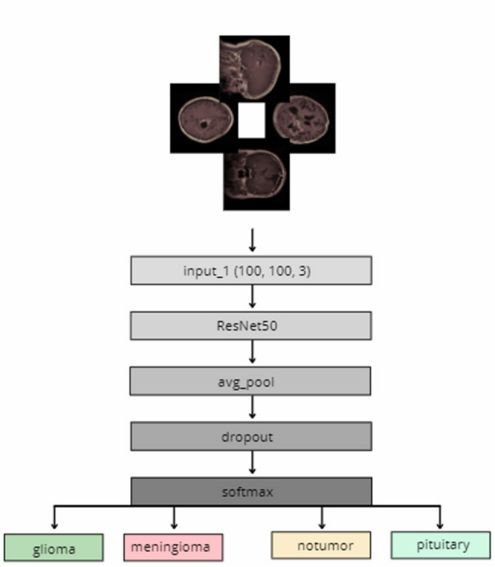

Figure 1. The Proposed Method Architecture

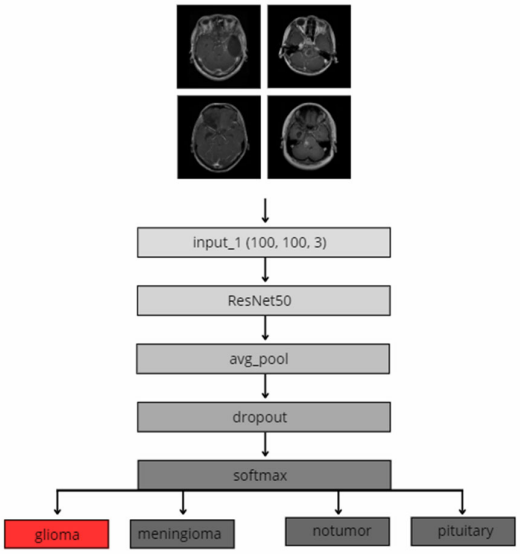

Figure 2. Glioma

Figure 2 shows the findings that emphasize the glioma type brain tumors. These findings demonstrate the model's capacity to effectively identify and categorize magnetic resonance imaging (MRI) associated with specific types of brain tumors, bolstering the validity and efficacy of the suggested classification strategy.

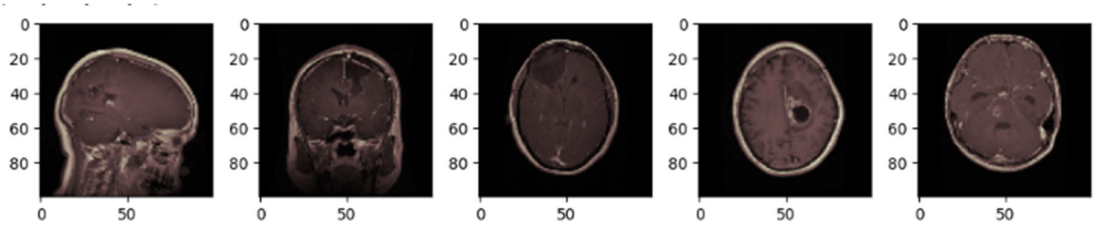

Figure 3. Dataset Image After Preprocessing

In this phase, each MRI image undergoes a series of preprocessing steps to enhance its quality and suitability for the model. These steps include bilateral filtering for noise reduction, color mapping for improved visualization, and resizing for consistency. The resultant images, as depicted below, demonstrate the effectiveness of the preprocessing techniques in preparing the data for subsequent stages of the classification pipeline.

```
# Fit the model
history = model.fit(datagen.flow(X_train, y_train_new, batch_size=32),
                    epochs=15,  # Increase the number of epochs as needed
                    validation_data=(X_valid, y_valid_new),
                    callbacks=[early_stopping, checkpoint])
```

```
Epoch 1/15
158/158 [==============================] - ETA: 0s - loss: 0.0511 - accuracy: 0.9818
158/158 [==============================] - 68s 427ms/step - loss: 0.0511 - accuracy: 0.9818 - val_loss: 0.0277 - val_accuracy: 0.9911
Epoch 2/15
158/158 [==============================] - 66s 416ms/step - loss: 0.0444 - accuracy: 0.9873 - val_loss: 0.0305 - val_accuracy: 0.9875
Epoch 3/15
158/158 [==============================] - 66s 418ms/step - loss: 0.0403 - accuracy: 0.9842 - val_loss: 0.0367 - val_accuracy: 0.9875
Epoch 4/15
158/158 [==============================] - 68s 426ms/step - loss: 0.0404 - accuracy: 0.9875 - val_loss: 0.0275 - val_accuracy: 0.9911
Epoch 5/15
158/158 [==============================] - 66s 418ms/step - loss: 0.0274 - accuracy: 0.9899 - val_loss: 0.0374 - val_accuracy: 0.9929
Epoch 6/15
158/158 [==============================] - 66s 418ms/step - loss: 0.0296 - accuracy: 0.9909 - val_loss: 0.0338 - val_accuracy: 0.9947
Epoch 7/15
158/158 [==============================] - 67s 425ms/step - loss: 0.0314 - accuracy: 0.9915 - val_loss: 0.0102 - val_accuracy: 0.9964
Epoch 8/15
158/158 [==============================] - 67s 425ms/step - loss: 0.0262 - accuracy: 0.9913 - val_loss: 0.0092 - val_accuracy: 0.9947
Epoch 9/15
158/158 [==============================] - 66s 418ms/step - loss: 0.0227 - accuracy: 0.9923 - val_loss: 0.0110 - val_accuracy: 0.9964
Epoch 10/15
158/158 [==============================] - 66s 417ms/step - loss: 0.0194 - accuracy: 0.9935 - val_loss: 0.0169 - val_accuracy: 0.9964
Epoch 11/15
158/158 [==============================] - 66s 418ms/step - loss: 0.0277 - accuracy: 0.9925 - val_loss: 0.0158 - val_accuracy: 0.9929
Epoch 12/15
158/158 [==============================] - 66s 418ms/step - loss: 0.0286 - accuracy: 0.9917 - val_loss: 0.0238 - val_accuracy: 0.9929
Epoch 13/15
158/158 [==============================] - 66s 418ms/step - loss: 0.0201 - accuracy: 0.9947 - val_loss: 0.0197 - val_accuracy: 0.9929
```

Figure 4. Model Training Results at 13th Epoch

The core of our method lies in the training of a sophisticated neural network, utilizing a pre-trained ResNet50 model as its backbone. After 13 epochs of training, the model exhibits outstanding performance metrics. With a loss of 0.0201, an accuracy of 99.47 percents, and a validation loss of 0.0197 coupled with a validation accuracy of 99.29 percents, our model surpasses expectations, showcasing its adeptness in capturing intricate patterns from brain MRI images.

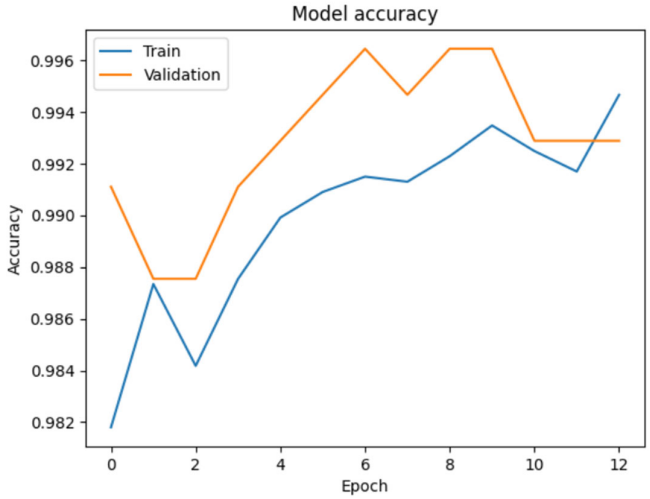

Figure 5. Graph of Increasing Training and Validation Accuracy

To visually understand the learning trajectory of our model, the graph of increasing training and validation accuracy over epochs provides invaluable insights. The upward trend signifies the model's continuous improvement in correctly classifying brain tumors as the training progresses, further reinforcing the efficacy of our approach

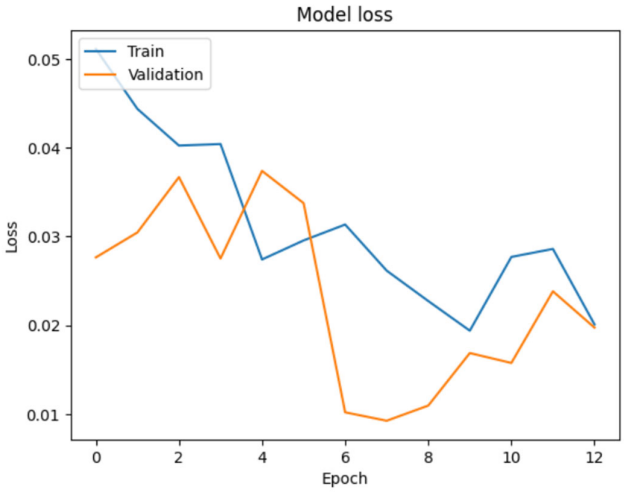

Figure 6. Graph of Decreasing Training and Validation Accuracy

In tandem with accuracy, monitoring the training and validation loss is crucial. The graph of decreasing training and validation loss showcases the model's efficiency in minimizing errors during the training process. The downward trend validates the model's capacity to generalize and make accurate predictions on unseen data

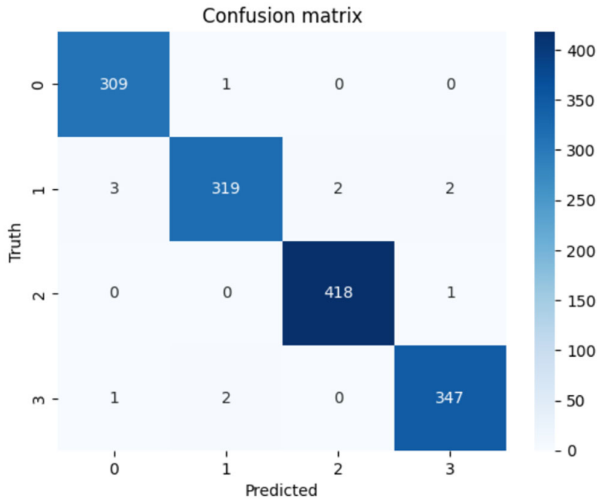

Figure 7. Graph of Confussion Matrix

The confusion matrix presented in the Figure 7 illustrates the classification performance of the proposed model on the test dataset consisting of four distinct classes: glioma (class 0), meningioma (class 1), pituitary (class 2), and no tumor (class 3). The model demonstrates a highly effective classification capability, notably achieving optimal performance for the pituitary class with only one misclassification out of 419 samples. Similarly, the glioma and no-tumor classes also exhibit strong predictive performance, each with just one misclassified sample. Conversely, the meningioma class displays a slightly higher error rate, with seven misclassifications out of 326 samples; however, this remains within an acceptable performance range. Overall, the confusion matrix reinforces the validity and reliability of the proposed convolutional neural network-based methodology in accurately classifying brain tumors from MRI images.

5. CONCLUSION

This study presents a comprehensive and robust brain tumor classification framework that leverages recent advances in deep learning and medical image analysis, with a particular focus on Convolutional Neural Network (CNN)-based methodologies. By integrating ensemble learning and employing pre-trained CNN models such as ResNet50, the proposed system effectively captures intricate features from brain MRI scans, facilitating a more accurate differentiation of tumor types. The application of data augmentation techniques enhances the model's generalization capability, especially in scenarios involving limited datasets, while also reducing the risk of overfitting.

In comparison to conventional machine learning approaches, the proposed CNN-based method demonstrates superior adaptability to the complex nature of medical imaging data. Traditional models often fall short in capturing the nuanced and hierarchical patterns present in brain MRI images, whereas the proposed approach achieves higher diagnostic accuracy by utilizing more advanced architectures and ensemble strategies.

The findings of this study establish a strong foundation for future research directions. Further improvements may include exploring more complex CNN architectures and incorporating larger and more diverse datasets to deepen the model's understanding of tumor variability. Moreover, integrating Explainable Artificial Intelligence (XAI) techniques could provide greater transparency in the model's decision-making processes, thereby enhancing clinical trust and interpretability. Collaborations with medical practitioners to incorporate domain-specific knowledge will be essential in refining the system for real-world clinical deployment.

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