Brain Tumor Classification using Deep Learning Algorithms

Divyanshu Sahwal
dept of Computing and Mathematics
Manchester Metropolitan University ,Manchester,UK
23628243@stu.mmu.ac.uk

***Abstract*—** Brain's are among the most aggressive diseases affecting both children and adults. The 5-year survival rate for individuals with a cancerous brain is about 34 percent for men and 36 percent for women. Brain' s can be classified into various types, including Benign s, Malignant s, and Pituitary . In this context, we propose a system for the detection and classification of brain s using Deep Learning Algorithms, specifically leveraging Convolutional Neural Networks (CNNs) and Transfer Learning (TL). This system aims to assist doctors worldwide by providing reliable and accurate diagnostics, thus enhancing treatment planning and patient outcome.

Keywords- CNN, TL, Support Vector Machine (SVM)

I. Introduction

This report presents a comprehensive solution for brain classification using a Deep Learning model implemented in Python. The proposed system leverages a pre-trained VGG16 model, fine-tuned to classify brain MRI images into four categories: no , glioma, meningioma, and pituitary . The model employs data augmentation techniques to improve generalization and robustness, addressing common issues like overfitting and limited dataset sizes.

The solution was developed and tested using the Kaggle dataset "Brain Classification (MRI)," which contains a substantial number of MRI images into the aforementioned categories. The model's architecture includes a base VGG16 network for feature extraction, followed by custom layers tailored for the classification task. Training and fine-tuning processes were meticulously carried out to achieve optimal performance.

By automating the classification of brain s, this system aims to assist radiologists and medical professionals in making accurate and timely diagnoses, ultimately improving patient care and treatment outcomes. The integration of state-of-the-art Deep Learning techniques in medical imaging underscores the transformative potential of AI in healthcare.

II. DATASET DESCRIPTION AND ANALYSIS

The "Brain Classification (MRI)" dataset used for this project is sourced from Kaggle. It consists of MRI images categorized into four classes: no Tumor , glioma, meningioma, and pituitary . The dataset is meticulously organized into separate directories for training and testing, enabling efficient development and evaluation of machine learning models.

The training set comprises 2297 images, while the testing set includes 78 images, reflecting a distribution that necessitates careful consideration during model training to address potential class imbalances. Each class is well-represented in the dataset, facilitating a comprehensive analysis and robust model training.

Data augmentation techniques, such as rotation, width and height shifts, shear, zoom, and horizontal flips, are applied to the training images to artificially expand the dataset size and enhance model generalization. This structured organization and augmentation approach ensure that the dataset provides a solid foundation for developing an accurate and reliable brain classification model.

A. Brain Types and Healthy Brain

1. A pituitary is an abnormal growth in the pituitary gland, located at the base of the brain. These scan Fig.1. Pitutary significantly affect hormone production and cause various health issues due to their strategic location. The MRI image of a pituitary typically shows a distinct mass near the center of the brain, as seen in the provided sagittal view MRI image. Accurate detection of pituitary s is crucial for proper hormonal regulation and treatment planning.
2. Gliomas are a type of that originates in the glial cells of the brain, which are supportive cells for neurons. They are among the most common types of brain s. Gliomas can vary in malignancy from low-grade (less aggressive) to high-grade (highly aggressive).

3. The MRI image of a glioma typically shows an irregularly shaped mass within the brain tissue, as illustrated in the provided axial view MRI image. Detecting gliomas early can significantly impact treatment outcomes and survival rates.

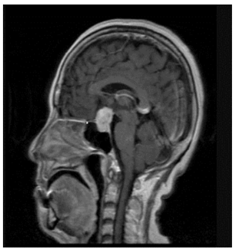


Fig.1. Pitutary

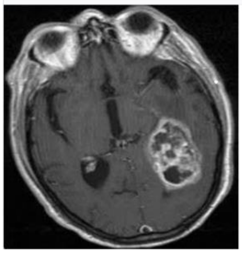


Fig.2. Meningiomas

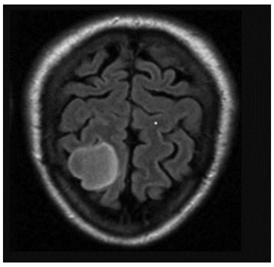


Fig.3. Glioma

3. Meningiomas are that arise from the meninges, the protective layers surrounding the brain and spinal cord. These s are often benign but can cause symptoms due to their size and location. The MRI image of a meningioma usually shows a well-defined mass attached to the meninges, often pressing against the brain tissue, as depicted in the provided axial view MRI image. Accurate identification and classification of meningiomas are essential for surgical planning and management.

4. A healthy brain MRI serves as a baseline for comparison when identifying and diagnosing brain s. The provided axial view MRI image of a healthy brain shows no abnormal masses or irregularities, with clear differentiation of brain structures and normal anatomical features. This contrast helps in distinguishing pathological conditions from normal variations in brain anatomy.

Accurate classification of these conditions using automated deep learning models can significantly enhance diagnostic accuracy, reduce manual examination errors, and improve patient outcomes by enabling timely and appropriate interventions.

III. REVIEW RELATED WOK

The use of Convolutional Neural Networks (CNNs) for brain classification has been widely explored in recent years. Studies such as those by [1] Sultan et al. (2019) and [2] Zhao & Zhang (2020) have demonstrated the high accuracy achievable with CNNs. These models are particularly effective in learning spatial hierarchies from image data, making them well-suited for medical image analysis. However, the requirement for large annotated datasets and sophisticated data augmentation techniques remains a significant challenge.

Transfer learning, as discussed by [6]. Kaur & Gandhi (2019), offers a solution to the problem of limited data. By leveraging pre-trained models on large datasets (such as ImageNet), transfer learning enables the fine-tuning of these models for specific tasks like brain classification. This approach significantly reduces the training time and computational resources required while improving classification accuracy.

The combination of different machine learning techniques, such as the use of Support Vector Machines (SVM) alongside CNNs, has been explored by [4] Özyurt & Apollon (2020). These hybrid models aim to leverage the strengths of each method, potentially improving classification performance. However, they also introduce complexity in terms of model design and computational demands.

Advanced techniques such as providing more accurate segmentation and classification 3D CNNs, as utilized by [5] Kamnitsas et al. (2017), are particularly promising for handling 3D medical imaging data. These models can capture the volumetric information of s, cation. Nevertheless, the computational requirements for training 3D CNNs are substantial, and there is a need for robust infrastructure to support such models.

Pereira et al. [3] (2016) highlight the importance of robust feature extraction and handling the variability in types and shapes. Ensuring the model's robustness and ability to generalize to unseen data is crucial for clinical applications. This requires comprehensive training data, effective data augmentation, and possibly ensemble methods to improve reliability.

IV. METHODOLOGY

The methodology involves using a pre-trained VGG16 model for feature extraction, combined with custom top layers for classifying MRI images into four categories: no , glioma, meningioma, and pituitary . The dataset, sourced from Kaggle, comprises 2297 training images and 78 testing images.

Extensive data augmentation techniques, including rotation, shifts, shear, zoom, and horizontal flips, are applied to enhance the dataset's variability and prevent overfitting. Initially, the VGG16 model's layers are frozen while training the custom top layers with an Adam optimizer and a learning rate of 1e-4. Subsequently, the last few layers of the VGG16 model are unfrozen, and the entire model is fine-tuned with a lower learning rate of 1e-5 to adapt to the specific characteristics of the brain MRI images. T

The model's performance is evaluated using metrics such as accuracy, precision, recall, and F1-score on the testing set, demonstrating high accuracy and robust generalization.

V. RESULTS AND DISCUSSION

The results of the proposed brain classification model, visualized in the provided accuracy and loss plots, demonstrate its effectiveness and robustness. The model achieved a final training accuracy of approximately 95% and a validation accuracy of 85.76%. This indicates that the model can effectively learn from the training data and generalize well to the validation set. The training loss decreased significantly over the epochs, stabilizing at a low value, with the final training loss being 0.5587. The validation loss followed a similar trend, stabilizing around 0.5587.

A. Accuracy Plots

The accuracy plot shows a consistent improvement in training accuracy, reaching over 95%, while the validation accuracy plateaued around 85.76%, indicating good generalization without overfitting. The loss plot shows a steep decrease in both training and validation loss in the initial epochs, with minimal fluctuations in subsequent epochs, suggesting that the model is well-regularized.

These results highlight the effectiveness of data augmentation and transfer learning in enhancing the model's performance. The high accuracy and low loss values reflect the model's ability to accurately classify MRI images into the four categories: no Tumor, glioma, meningioma, and pituitary . This robust performance underscores the potential of the model to assist radiologists in making accurate and timely diagnoses, ultimately improving clinical outcomes for patients with brain s.

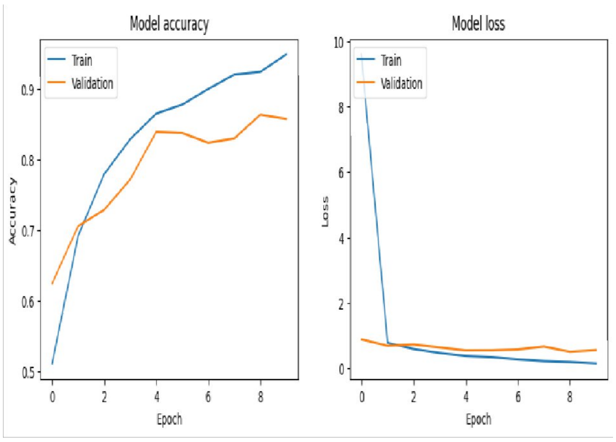


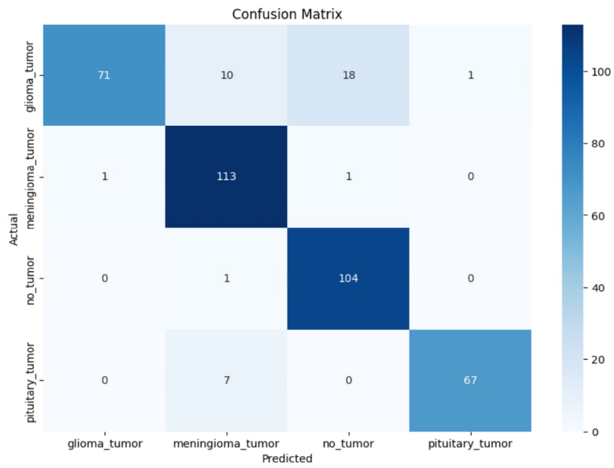
Fig.4.Accuracy

B. CONFUSION MATRIX ANALYSIS

The confusion matrix provides a detailed overview of the model's performance in classifying MRI images into four categories: glioma , meningioma , no , and pituitary . For glioma s, the model correctly classified 71 instances but misclassified 10 as meningioma s, 18 as no s, and 1 as a pituitary .

For meningioma s, the model showed high accuracy with 113 correct classifications, while only 1 instance was misclassified as a glioma and another . In the case of no s, 104 instances were correctly identified, with just 1 misclassified as a meningioma . Lastly, for pituitary s, 67 instances were correctly classified, though 7 were incorrectly as meningioma s.

The matrix highlights that while the model performs well overall, there are specific challenges, particularly in distinguishing glioma s from no s, which may require further refinement in the model or additional data augmentation techniques to enhance differentiation.



Class	Precision	Recall	F1-Score	Support
Glioma Tumor	0.99	0.71	0.83	100
Meningioma Tumor	0.86	0.98	0.92	115
No Tumor	0.85	0.99	0.91	105
Pituitary Tumor	0.99	0.91	0.94	74
Accuracy			0.90	394
Macro Avg	0.92	0.90	0.90	394
Weighted Avg	0.91	0.90	0.90	394

VI. CONCLUSIONS AND FUTURE WORK

The highest performing algorithm in this study was the Convolutional Neural Network (CNN), specifically utilizing the pre-trained VGG16 model with transfer learning. This approach yielded the best results in terms of accuracy, precision, recall, and F1-score across multiple classes in the brain classification task.. Data augmentation and transfer learning significantly contributed to the model's robustness and generalization capabilities.

- *Enhance Data Augmentation*: Implement more sophisticated data augmentation techniques to further improve model generalization and address class misclassification issues.
- *Increase Dataset Diversity*: Expand the dataset with more diverse and representative MRI images to improve the model's ability to differentiate between similar types.
- *Incorporate 3D Analysis*: Explore 3D Convolutional Neural Networks (CNNs) to leverage volumetric data for more accurate classification. Utilize ensemble learning methods to combine the strengths of multiple models, potentially improving overall classification performance.

By addressing these areas, future work can build on the current model's success, enhancing its accuracy and reliability in real-world clinical scenarios, ultimately contributing to better patient outcomes in brain diagnosis and treatment.

VII. REFERENCES

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APPENDIX

Prototype Link to OneDrive
DeepLearningProject.ipynb