Brain Tumor Classification through MRI image analysis

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PR Semester Project

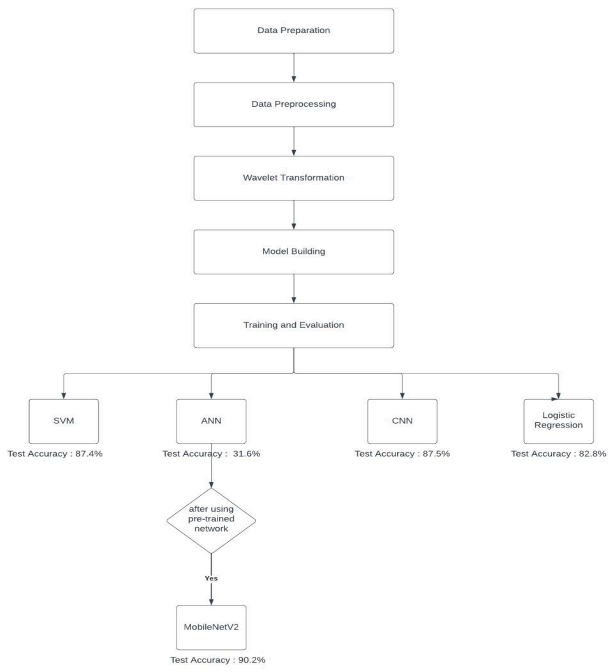
***Abstract*: This project employs deep learning and image processing to classify brain tumours. Extracting archives, building models (ANN, CNN, SVM, Logistic Regression), and incorporating wavelet transformations, it achieves accurate classification, providing a comprehensive solution for brain tumour image analysis.**

***Keywords*:** Brain tumor, Wavelet Transformation, Artificial Neural Networks(ANN), Convolutional neural network(CNN), Support vector machines(SVM), Logistic Regression, MobileNetV2.

I. Introduction

Brain tumors are regarded as a fatal condition that impacts the lives of so many people worldwide . The kind, location, and size of a brain tumor all affect how it will be treated. There are several forms of brain tumours, some of which are benign (non-cancerous), while others are malignant (cancerous). A benign tumor commonly referred to as a low-grade tumour does not significantly harm surrounding healthy tissues. On the other hand, a benign tumour is the contrary of a malignant tumour; in this case, the tumor cells directly cause the person’s death and they can readily disseminate across the surrounding brain tissues. They are also known as high-grade tumors. One of the most prevalent tumor forms that develop in the brain and have the greatest fatality rate is glioma, which accounts for around 33% of all brain tumours. Gliomas can be classified into several categories based on their propensity for development and level of severity. This project endeavours to revolutionize brain tumour detection by leveraging a robust set of technologies and methodologies. It begins with meticulous data handling, segmenting MRI images into distinct training and testing sets. Preprocessing techniques, including grayscale conversion and standardizing image dimensions (240x240 pixels), ensure data uniformity for subsequent analysis. The implementation harnesses the power of Logistic Regression and Support Vector Machines (SVM), prominent machine learning models, for precise brain tumour classification. Rigorous evaluation through accuracy metrics scrutinizes the models' performance and their ability to generalize to new data. Visual representations vividly showcase the models' predictions, aiding in comprehension of their decision-making processes. Further analysis includes dissecting misclassified samples, unravelling insights into model limitations. This comprehensive approach aims to contribute significantly to the field of medical diagnostics, specifically in enhancing brain tumour detection through innovative technology and computational methods.

II. Block Diagram



III. Methodology

1. Data Preprocessing

Data preprocessing involves rescaling and normalization of images using the ImageDataGenerator in TensorFlow. Rescaling is achieved through dividing pixel values by 255. This process ensures uniformity in pixel scales, facilitating effective model training. Additionally, the code employs techniques like rotation, brightness adjustment, and horizontal flipping, enhancing the dataset through data augmentation.

2. Data Augmentation

The ImageDataGenerator is utilized for data augmentation in the code. It introduces variability into the training dataset by applying transformations like rotation, brightness adjustment, and horizontal flipping. These augmented images contribute to a more diverse dataset, preventing overfitting and improving the model's ability to generalize to unseen data.

3. Feature Extraction

Wavelet analysis is a powerful method for feature extraction in image processing. In the provided code, the 'bior1.3' wavelet is applied after converting the image to grayscale. This process decomposes the image into four components, capturing both low and high-frequency details in horizontal and vertical directions. These components serve as distinctive features for tasks like image compression and pattern recognition. The grayscale conversion is essential to focus on structural details rather than color.

4. Data Visualisation

The code incorporates data visualization techniques using pie charts and bar graphs to illustrate the distribution of different tumour types in the training and testing datasets. This exploratory data analysis aids in understanding class imbalances and guides decisions related to data sampling and representation.

5. Artificial Neural Network

The code implements an Artificial Neural Network (ANN) using the Sequential API from Keras. The architecture consists of flattened input layers, dense hidden layers with ReLU activation functions, and an output layer with SoftMax activation for multiclass classification. The model is compiled with the Adam optimizer and categorical cross-entropy loss function, suitable for the provided multi-class tumour classification task. Training involves multiple epochs with early stopping based on loss.

6. Convolutional Neural Networks

The CNN model is constructed using the Sequential API, incorporating convolutional layers, max-pooling layers, and fully connected layers. The model architecture is designed to capture hierarchical spatial features in image data. Training involves multiple epochs, and the model's performance is monitored using callbacks, including early stopping.

7. Support Vector Machines

SVMs are versatile classifiers. In the context of image classification, they can be implemented using libraries like scikit-learn. SVMs excel in handling non-linear relationships in feature space and can be a valuable alternative or complement to deep learning approaches.

8. Logistic Regression

logistic regression serves as a foundational classification algorithm. It is interpretable, computationally efficient, and suitable for binary or multi-class problems. Logistic regression can serve as a benchmark model for comparison with more complex architectures.

9. MobileNetV2 (Pertained Network)

The code demonstrates the integration of MobileNetV2, a lightweight ANN architecture designed for mobile and edge devices. The model is pre-trained on ImageNet and fine-tuned for the specific brain tumour classification task. MobileNetV2 offers a balance between computational efficiency and accuracy, making it suitable for real-time applications.

IV. Results

The experiments encompassed various machine-learning models for brain tumour classification. Notably, the MobileNetV2 pre-trained model with ANN surpassed all others, demonstrating exceptional accuracy on both training and testing datasets, achieving an impressive score of **90.2%.** Followed by MobileNetV2, the Convolutional Neural Network (CNN) model showcased commendable performance, obtaining an accuracy score of **87.5%.** However, the Support Vector Machine (SVM) and Logistic Regression models trailed behind, demonstrating considerable accuracies with scores of **87.4%** and **82.85%**, respectively. Conversely, the artificial neural network (ANN) showed a notably lower accuracy of **31.64%.** To boost its accuracy and lower errors, we teamed it up with MobileNetV2, a pretrained network that already knows a lot about images. This collaboration helps the ANN get better at recognising things. A detailed examination of misclassified samples offered insights into the models' limitations. MobileNetV2 emerged as the frontrunner, showcasing superior capabilities in accurately classifying brain tumour types, surpassing CNN, SVM, Logistic Regression, and the deliberately lower-performing ANN. But give good Accuracy after using a ANN with a pertained network MobileNetV2.

S.No	Training Model	Testing Accuracy
1.	Artificial Neural Network	**31.64%**
2.	Convolutional Neural Networks	**87.5%**
3.	Support Vector Machines	**87.4%**
4.	Logistic Regression	**82.85%**
5.	ANN+MobileNetV2	**90.2%**

V. Conclusion

Exploring different machine learning models for brain tumor classification has revealed important findings. Using pre-trained models like MobileNetV2 has proven to be a game-changer, especially in using prior knowledge for better medical image analysis. This goes beyond just looking at accuracy scores and emphasizes the importance of pre-trained models in handling complex tasks with limited data.

Despite competitive performances from models like CNN, SVM, and Logistic Regression, there are still challenges in understanding subtle details in brain tumor images. This journey has shown how AI in healthcare is always changing and improving. It highlights the need for ongoing innovation in how models are built and how easily they can be understood.

In the end, what we've learned from this project is the close relationship between what we already know, how algorithms are getting better, and the constant effort to improve accuracy in analyzing medical images.

This whole experience stresses the importance of continuously enhancing computer methods in healthcare. It's not just about the numbers; it's about understanding how these models function and finding better ways to assist doctors in making accurate diagnoses from medical pictures.