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ADVANCING MULTI-MODAL BRAIN TUMOR CLASSIFICATION AND EXPANDING BEYOND TRADITIONAL CATEGORIES

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Abstract

Recent developments in computer vision and machine learning have greatly enhanced medical image analysis, particularly in the field of identifying and categorizing brain tumors. This study explores various deep learning models' effectiveness for multi-modal brain tumor classification, considering a dataset comprising 4,478 MR images categorized into 44 distinct classes, including diverse brain tumor types and normal brain images. The research focuses on meticulous data preprocessing, leveraging pre-trained convolutional neural networks (CNNs), and employing transfer learning to fine-tune model architectures. Comprehensive experiments involving model training, validation, and testing reveal the effectiveness of models such as EfficientNetB5, ResNet50, VGG16, VGG19, MobileNetV3, DenseNet201, and InceptionV3. Evaluation criteria such as F1-score, accuracy, precision, and recall show how well the models perform across a range of brain tumor classes. The study highlights the superiority of the EfficientNetB5 model in achieving an accuracy of 95%, showcasing its potential as a cost-effective and reliable tool for assisting radiologists in brain tumor diagnosis. The results aim to promote early and accurate brain tumor diagnosis for better patient care by improving the efficiency and accuracy of deep learning models for brain tumor categorization.

Keywords – Tumor Classification, Deep Learning, Convolutional Neural Networks (CNNs), Medical Image Analysis, EfficientNetB5, Multi-modal Imaging, Transfer Learning.

Introduction

Improvements have been noticeable in machine learning and computer vision techniques. medical image classification over the last two decades. Within medical imaging, machine learning techniques excel in training model parameters based on specific features within images. These learned models are then applied to predict these features, effectively tackling classification, regression, and segmentation challenges in medical imaging.

In the field of modern medicine, various advanced medical methods, including CT scans, ECGs, and MRIs, play a crucial role in the diagnosis of serious disorders, including brain tumors, heart attacks, and cancer. Deep learning has shown to be a useful technique in the artificial intelligence space for working with medical specialists. Its role involves the analysis of patients' conditions and the recommendation of suitable treatments. Moreover, it contributes to the discovery and development of new medications. By reviewing a patient's medical history, treatment decisions can be tailored to individual needs, harnessing the power of deep learning to gain insights from test results, reports, and symptom-related information, thereby enhancing healthcare. Furthermore, the comprehension of tumors is fundamental in the medical landscape. A tumor is any anomalous mass produced by aberrant or unchecked cell proliferation. Over the past couple of decades, healthcare experts have discovered more than 120 distinct forms of brain tumors. These tumors can be divided into two main categories: primary brain tumors, originating within the brain's tissue, and secondary brain tumors, which manifest within the brain but originate from different bodily regions.

Brain tumors, comprising cancerous cells, possess the capacity to infiltrate and fatally affect brain tissue. These tumors vary widely in size, ranging from minuscule to substantial masses. Certain brain tumors, due to the immediate onset of noticeable symptoms, are detected at an early stage while they are still small. There are cases where some brain tumors grow substantially before they are recognized. The expansion of these tumor masses within the confines of the skull disrupts normal brain functionality. If left undetected in the initial stages, this interference with brain function can pose life-threatening risks. Early detection becomes crucial in mitigating the potential dangers associated with such tumors.

For timely treatments, brain cancers must be detected early. Deep learning has been applied to medical imaging to detect local anatomical features, identify organs and body components, and recognize cells of different sizes and shapes. Promising results in the segmentation and classification of medical pictures can be obtained by the application of deep learning. It increases the automation of noninvasive imaging-based diagnosis. Medical practitioners often favor noninvasive imaging methods such as CT scans, MRIs, and X-rays are used to identify and categorize brain cancers. Presently, the majority of detection and diagnostic methods depend on radiologists' and neurospecialists' interpretation of images, which can be labor-intensive and susceptible to human error Symptoms of brain tumors, such as headaches, seizures, neurological issues, nausea, vomiting, and others displayed in Figure 1. The severity of these varies based on the location and size of the tumor can affect the symptoms within the brain. It's vital to note that certain symptoms might be common across different types of tumors.

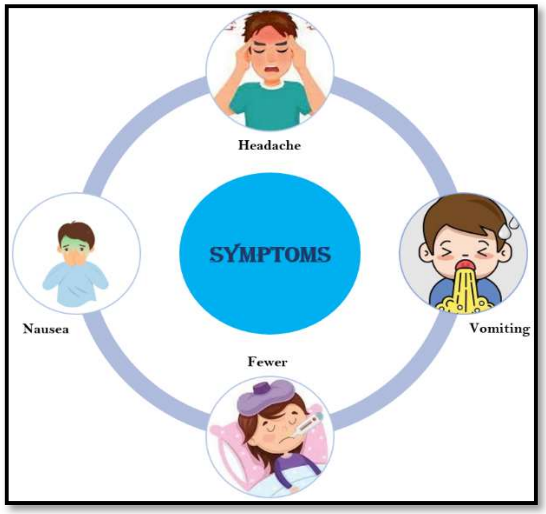

Fig.1: Common Symptoms of Brain Tumor Patients

The location-specific tumor symptoms depicted in Figure 2 could be a crucial indicator of the patient's prognosis. For instance, tumors in the frontal lobe may result in personality changes, cognitive difficulties, or even weakness on one side of the body. On the other hand, tumors in the parietal lobe might cause sensory disturbances and problems with coordination, whereas those in the occipital lobe may predominantly affect a patient's eyesight. It is essential to comprehend these site-specific symptoms to make an accurate diagnosis and choose the optimal course of treatment for patients with brain tumors. The integrated approach, harnessing advanced imaging technologies and deep learning models, is revolutionizing brain tumor diagnostics, opening the door to more individualized treatment approaches and improved patient outcomes.

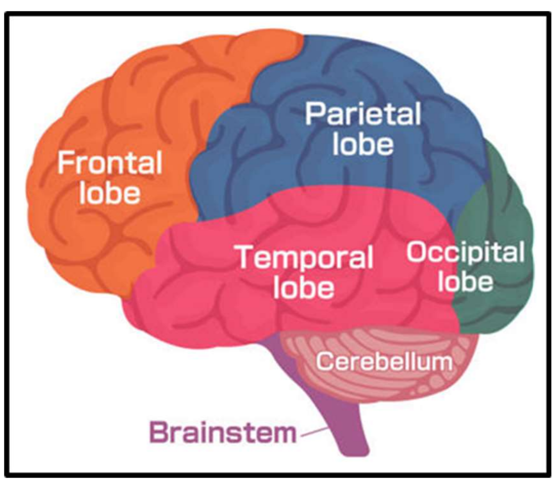

Fig.2: Anatomy of Brain Lobes in Brain Tumor

Literature Review

Recent advances in applying convolutional neural networks to analyze MRI scans have revolutionized the precision of brain tumor diagnosis in medical imaging. This related work provides an overview of recent advancements utilizing convolutional neural networks (CNNs) in accurately classifying and using magnetic resonance imaging (MRI) scans to identify brain cancers.

Chetana Srinivas et al. (2022) [1] explored the ability of deep transfer learning techniques to accurately identify brain cancers from MRI pictures. They made use of convolutional neural networks (CNNs) that were already in existence, including Inception-v3, ResNet-50, and VGG-16. The research focuses on improving medical diagnostics, especially the accurate diagnosis of brain cancers using MRI imaging. Their findings highlight the significance of deep learning for enhancing medical diagnostics, particularly brain tumor identification.

Ejaz Ul Haq et al. (2022) [2] focused on a hybrid methodology integrating Tumor segmentation and classification in brain magnetic resonance imaging (MRI) using deep convolutional neural networks (CNN) and machine learning classifiers. This study explored an innovative fusion of these technologies to increase the precision and effectiveness of brain tumor detection, emphasizing advancements in medical image analysis for enhanced diagnostic capabilities.

Mamoona Humayun et al. (2022) [3] focused on utilizing a feature selection method in conjunction with deep learning techniques for image classification within the realm of medical imaging. They presented an innovative approach that combines deep learning algorithms with a specialized feature selection process to enhance the accuracy and efficiency of image classification tasks. They proposed a framework that optimizes the selection of features relevant to the specific medical imaging context, thereby improving the effectiveness of deep learning models in correctly classifying pictures related to medicine.

Sahar Gull et al. (2021) [4] emphasized the application of deep learning methodologies, specifically CNNs, to develop an automated system for detecting and classifying brain cancers using MRI data. By utilizing advanced algorithms, the research seeks to improve the precision and effectiveness of brain tumor detection, an essential aspect of medical diagnosis and treatment planning.

Sarang Sharma et al. (2022) [5] demonstrated the efficacy of their deep learning model in effectively categorizing brain tumors, showcasing its potential for automated classification and prediction tasks. This research contributed to the growing field of medical imaging and computer-aided diagnosis by offering a solution that streamlines and improves the diagnostic process for brain tumors.

Tahia Tazin et al. (2021) [6] focused on enhancing brain tumor classification accuracy using advanced deep-learning techniques tailored for medical image analysis. By Utilizing CNNs, the study significantly contributes to establishing a dependable technique for accurately classifying brain tumors, showcasing encouraging outcomes in automating diagnoses based on medical imaging data. This approach underscores the potential of CNN-based methodologies in transforming the precise and effective categorization of brain cancers, offering a significant stride toward improved diagnostic capabilities in healthcare.

Thanh Han-Trong et al. (2022) [7] suggested a successful strategy for identifying brain cancers. Employing Deep Convolutional Neural Networks (CNNs) and MRI images, their approach aims to enhance accuracy in tumor diagnosis. The study demonstrated the effectiveness of CNNs in automating brain tumor diagnosis through advanced image analysis techniques.

Hareem Kibriya et al. (2022) [8] presented a model for classifying brain tumors. Their method utilizes deep feature fusion in conjunction with well-known machine learning classifiers to improve the precision of brain tumor classification. By integrating deep learning techniques with established classifiers, the study presented a reliable and efficient method for accurately classifying brain tumors, offering potential advancements in automated diagnostic tools for medical imaging and aiding in accurate tumor identification from imaging data.

In this review, we examine how recent developments in deep learning methods and medical imaging have affected brain tumor diagnosis in a big way. The survey examines the latest research endeavors focusing on the utilization of deep learning methodologies, particularly convolutional neural networks (CNNs), to precisely use Magnetic Resonance Imaging (MRI) data for brain tumor detection and classification. This overview highlights key studies investigating diverse strategies such as transfer learning, feature fusion, and the integration of CNNs with machine learning classifiers, aiming to transform the landscape of medical diagnostics for brain tumors.

Dataset Description

The Kaggle website provided the dataset that was utilized in this study. By Fernando Feltrin comprises 4,478 MR Images which in an imbalanced state of brain tumors, meticulously categorized There are fourteen different forms of brain tumors, which include oligodendroglioma, papilloma, schwannoma, astrocytoma, carcinoma, ependymoma, ganglioglioma, germinoma, glioblastoma, granuloma, medulloblastoma, meningioma, neurocytoma, and tuberculoma.

Each of the 14 types of brain tumors in the dataset is further divided into three subtypes, each represented by T1-weighted, T1CE, and T2-weighted MR images in JPEG format. This subdivision results in a total of 42 classes [21], allowing for a more detailed grouping of brain tumors according to their nature and imaging features.

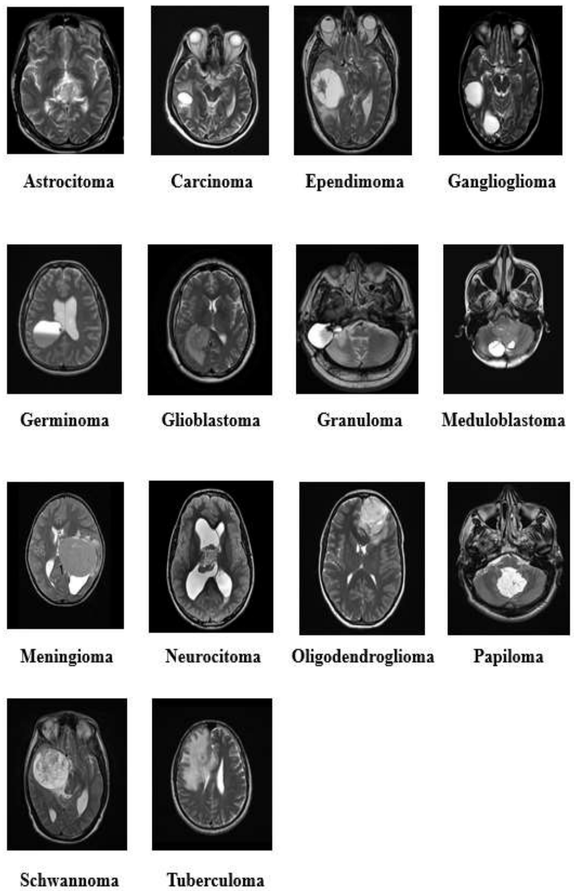

Fig.3: A Visual Overview of 14 Distinct Tumors.

In addition to these 42 classes, the dataset also includes two more classes representing normal images, which consist of T1-weighted and T2-weighted images of healthy brain tissue. This addition brings the total number of classes available for classification to 44, providing a comprehensive set of categories for differentiating between various types of brain tumors and normal brain tissue in MRI images.

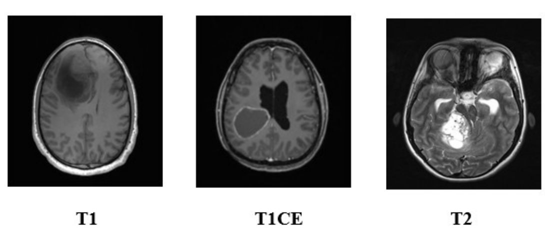

Fig.4: Three multisequence MR images.

Methodology

The dataset used in our brain tumor classification study was procured via Kaggle, consisting of 4,478 MR images categorized into 44 classes. These classes show both normal brain imaging and different kinds of brain cancers. Each class was meticulously organized into three categories, with each category consisting of three subtypes: T1-weighted, T1CE, and T2-weighted images. Additionally, two more classes were included to represent normal brain images, resulting in a total of 44 classes for classification.

To prepare the brain tumor image dataset for machine learning model training, extensive preprocessing steps were undertaken. These steps ensured data uniformity and suitability [9] for training a deep learning model.

Image resizing was performed to standardize the image dimensions across the dataset. Every image was resized to 224 x 224 [10] pixels, which was a standard size with three color channels (RGB). This standardization ensures that all images share the same dimensions, a prerequisite for training deep learning models.

To improve the training dataset's diversity and the model's capacity for generalization, data augmentation approaches were used. Horizontal flipping was employed as a data augmentation technique, introducing variability to the training set without requiring additional data collection efforts in such a way the flow of architecture was given in figure 5.

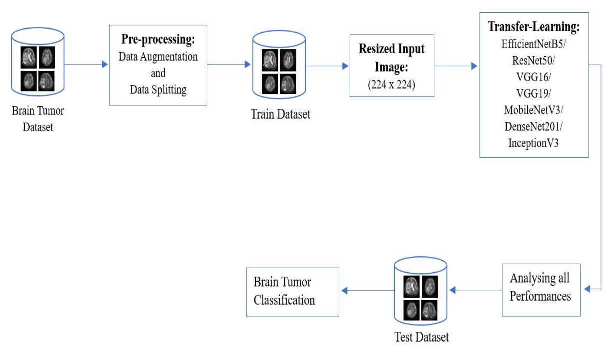

Fig.5: Model Architecture.

The preprocessed dataset was split into three subsets: training, validation, and testing. Stratified sampling was employed to maintain an even distribution of the 44 classes across each subset. This stratified approach was crucial to avoid bias and ensure that the model had an equal opportunity to learn from every class [11].

Thoroughly dividing the dataset into sets for testing, validation, and training allowed for the development and assessment of viable models. This method made sure the model was evaluated on an unknown set to gauge its capacity for generalization and trained on a representative sample of the data.

The precise proportion of 15% for testing, 70% for training, and 15% for validation ensured a balanced distribution of classes in each subset. This balanced distribution enhanced the generalization and consistent performance of the model across various brain tumor types and normal images [12]. By implementing these comprehensive preprocessing steps, the brain tumor image dataset was transformed, and the brain tumor image dataset was transformed the model's generalizability and steady performance.

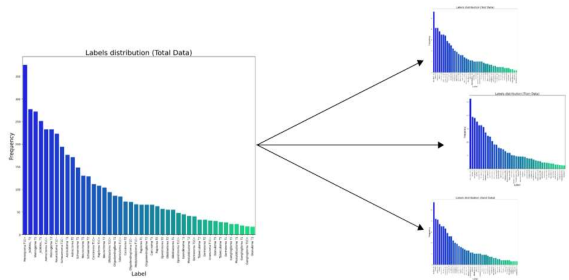

Fig.6: Train, Test, and Validation Sets Utilizing Stratified Sampling.

The neural network's architecture is the basis of the brain tumor categorization system [13]. Choose a Deep Neural Network architecture as our backbone to design a robust model. The ImageNet dataset served as the model's pre-training set. and is known for its efficiency in depth and width scaling, making it well-suited for our task. We added multiple layers to the pre-trained EfficientNetB5 model. to fine-tune its performance.

Conducted hyperparameter tuning for each model to optimize its performance. This involved configuring parameters [13] related to regularization, activation functions, dropout rates, and learning rates specific to each model.

Batch Normalization [15] was employed to stabilize and expedite the training process. This technique normalizes the inputs of a layer, minimizing internal covariate shifts and enabling more effective and efficient training. Batch Normalization contributes to the model's overall stability and generalization performance.

To prevent overfitting, Dense Layers were integrated with kernel and activity regularization [16]. These regularization techniques constrain the complexity of the learned patterns, preventing the model from becoming overly tailored to the training data. The introduction of appropriate regularization parameters in the dense layer balances model complexity with generalization performance.

Dropout Layers [17] were used to reduce overfitting tendencies. During training, these layers deactivate a fraction of neurons at random, preventing the model from depending too heavily on specific neurons. Dropout Layers improve the model's generalization capabilities by incorporating this element of unpredictability, guaranteeing that it performs well on both training and unseen data.

The last layer connects the output of the model to an activation function of softmax that is dense. The classifier is this last layer, generating probability distributions across the various class labels. The softmax activation function ensures that the model's predictions are well-calibrated probabilities, allowing for accurate classification label prediction.

The combination of Batch Normalization, Final Dense Layer with Softmax activation results, Dropout Layers, and Dense Layers with Regularization in a well-optimized and regularized neural network model. Each component contributes to training stability, reducing overfitting, and allowing the model to generate accurate predictions across a wide variety of classes.

For the development of an efficient brain tumor classification model, we employed a diverse set of neural networks with pretraining convolutional (CNNs), each serving as the base architecture. Our approach involved leveraging the knowledge captured by these well-established models, including EfficientNetB5, ResNet50, VGG16, VGG19, MobileNetV3, DenseNet201, and InceptionV3 [18].

To tailor the pre-trained models for our classification task, we augmented them with a custom classification head. This head consisted of densely connected layers that learned to classify brain tumor images into the designated categories. The classification head was designed to adapt the high-level features obtained from the convolutional base to our specific classification requirements [19].

The brain tumor dataset was used to independently train each model, and its accuracy and loss were assessed. The dataset, as previously stated, consists of a total of 44 classes, including brain tumor types and normal brain images.

The performance of each pre-trained model was meticulously compared to determine which architecture yielded the most accurate and reliable results for brain tumor classification. This comparison provided insightful information on the advantages and disadvantages of each plan.

Results and Discussion

Seven pre-trained CNN models, including EfficientNetB5, ResNet50, VGG16, VGG19, MobileNetV3, DenseNet201, and InceptionV3, are used in an experimental evaluation for the detection of BT from MR images. The MR images gathered from the brain tumor Dataset were used to create the CNN models. Approximately 3205 photos were used for training, 687 images for testing, and 687 images for validation. The original resizing of the brain MR pictures was 224 × 224. Each model has its unique architectural characteristics and was pre-trained on large-scale image datasets.

To harness features extracted by these pre-trained models, we froze the convolutional base of each architecture. This decision was pivotal in ensuring that the models retained their learned knowledge from the original datasets while adapting to the specific task of brain tumor classification.

Transfer learning was used in the implementation of each algorithm. 32 batches [20] were used to train the models. over 100 epochs, ensuring that almost all samples were utilized in the training process by setting the parameter "steps per epoch" to 20.

An early stopping mechanism and model checkpointing were added to the implemented methodology during the neural network model's training. A monitoring criterion based on the validation loss was used in conjunction with early halting. To avoid overfitting, the training process was specifically stopped if the validation loss did not demonstrate progress for a predetermined patience of 5 epochs.

Concurrently, model checkpointing was put into place to preserve the model's weights while minimizing validation loss. This was accomplished by setting up a Model Checkpoint callback that ran in "minimization" mode, tracked the validation loss, and saved just the best weights.

Using a batch generator “train_gen” with a 98-step step size, the model was trained across 100 epochs. These tactics were essential for maintaining the best-performing model weights for further study or deployment, avoiding overfitting, and maximizing model performance.

The sequential approach was expanded with several layers, first a dense layer consisting of 256 units, and then batch normalization to enhance training stability. To avoid overfitting, regularization approaches such as L2 kernel regularization and L1 activity and bias regularization were used. The rectified linear unit (ReLU) activation function was applied to introduce non-linearity. The addition of a dropout layer with a rate of 0.45 enhanced generalization even more by lowering the likelihood of overfitting during training. The model was completed with a dense layer whose output size matched the target class count and which employed the SoftMax activation function for multi-class classification.

The Adamax optimizer was used for optimization and has a 0.001 learning rate. Accuracy was selected as the evaluation metric, Conversely, the loss function selected was categorical cross-entropy. A thorough description of the network's parameters and structure was provided by the `model.summary()` function, which detailed the model architecture and setup.

Performance measurements are derived from the True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) features of the confusion matrix.

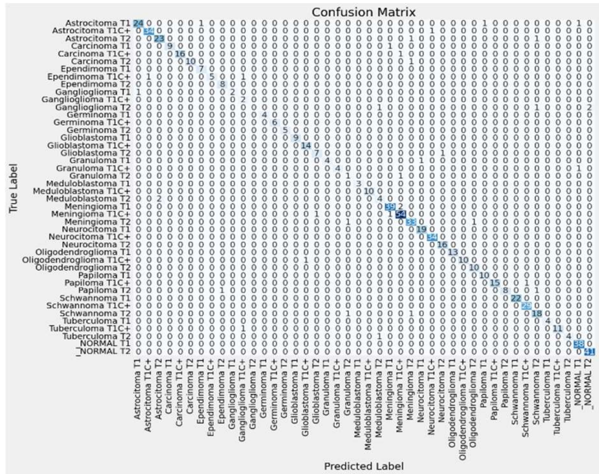

Fig.7: Confusion matrix encompasses all 44 classes.

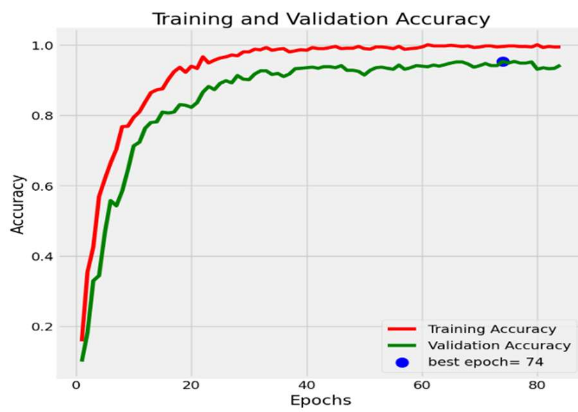

Fig.8: EfficientNet B5 model's accuracy curve.

The model's ultimate test came with the evaluation of the testing dataset. The results were highly promising, with a reported test accuracy of approximately 94.37%.

This indicated the model's capacity to accurately classify brain tumor images across the 44 distinct classes. The low test loss further emphasized the model's effectiveness.

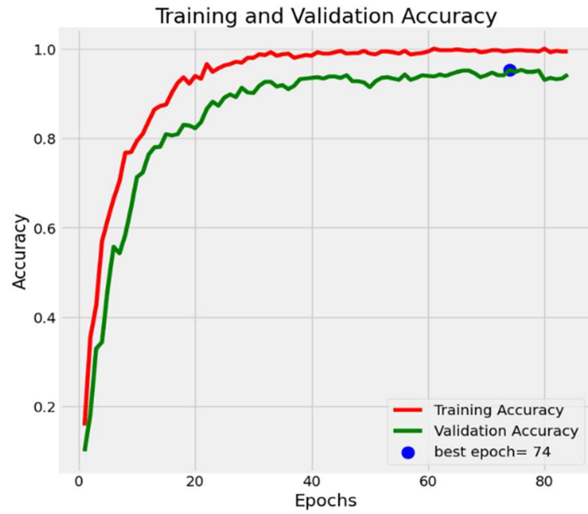

Fig.9: EfficientNet B5 model's Loss curve.

Despite these challenges, the model achieves a remarkable overall accuracy of 95%, demonstrating its ability to make correct predictions with a high degree of consistency.

Both macro and weighted average metrics reinforce this consistent performance across diverse classes, giving a thorough rundown of the robustness of the model.

The combination of transfer learning, a batch size of 32, and 100 epochs during training has yielded promising results across a wide range of brain tumor classes.

The well-balanced precision, recall, and F1 scores further affirm the ability of the model to accurately discriminate between various tumor kinds.

Class Labels	precision	Recall	F1-Score	Support
Astrocitoma T1	0.96	0.89	0.92	27
Astrocitoma T1C+	0.97	0.97	0.97	35
Astrocitoma T2	0.92	0.92	0.92	25
Carcinoma T1	1	0.9	0.95	10
Carcinoma T1C+	1	0.94	0.97	17
Carcinoma T2	1	0.91	0.95	11
Ependimoma T1	0.88	1	0.93	7
Ependimoma T1C+	1	0.71	0.83	7
Ependimoma T2	0.89	1	0.94	8
Ganglioglioma T1	1	0.67	0.8	3
Ganglioglioma T1C+	0.5	1	0.67	2
Ganglioglioma T2	0	0	0	4
Germinoma T1	1	1	1	4
Germinoma T1C+	1	1	1	6
Germinoma T2	1	1	1	5
Glioblastoma T1	1	1	1	9
Glioblastoma T1C+	0.93	1	0.97	14
Glioblastoma T2	0.88	0.88	0.88	8
Granuloma T1	1	0.8	0.89	5
Granuloma T1C+	1	0.8	0.89	5
Granuloma T2	0.33	0.5	0.4	2
Meduloblastoma T1	1	1	1	3
Meduloblastoma T1C+	1	1	1	10
Meduloblastoma T2	0.67	0.67	0.67	6
Meningioma T1	0.95	0.95	0.95	41
Meningioma T1C+	0.93	0.96	0.95	56
Meningioma T2	0.92	0.94	0.93	35
Neurocitoma T1	0.95	1	0.97	19
Neurocitoma T1C+	0.97	1	0.99	34
Neurocitoma T2	0.94	1	0.97	16
Oligodendroglioma T1	1	1	1	13
Oligodendroglioma T1C+	1	0.91	0.95	11
Oligodendroglioma T2	0.91	1	0.95	10
Papiloma T1	0.91	1	0.95	10
Papiloma T1C+	1	0.94	0.97	16
Papiloma T2	1	0.8	0.89	10
Schwannoma T1	1	1	1	22
Schwannoma T1C+	0.97	1	0.98	29
Schwannoma T2	0.86	0.9	0.88	20
Tuberculoma T1	1	1	1	4
Tuberculoma T1C+	1	0.92	0.96	12
Tuberculoma T2	1	0.8	0.89	5
_NORMAL T1	0.95	1	0.97	38
_NORMAL T2	0.95	1	0.98	41
accuracy			0.95	675
macro avg	0.91	0.9	0.9	675
weighted avg	0.94	0.95	0.94	675

Fig.10: Classification Report.

The model's remarkable capacity to accurately identify cases of certain tumor kinds is demonstrated by the precision, recall, and F1-scores of 1.0 displayed by these classes.

While the model exhibits impressive overall accuracy, certain tumor classes, such as "Ganglioglioma T2" and "Granuloma T2," pose challenges, as indicated by reduced F1 scores, recall, and precision. This indicates regions in which the model's functionality could be improved through further refinement.

Conclusion

This work presents a comprehensive evaluation of the seven most effective D.L models for BT detection, including EfficientNetB5, ResNet50, VGG16, VGG19, MobileNetV3, DenseNet201, and InceptionV3. When compared to other models, the EfficientNetB5 model produces the best results. The outcomes show how effective the EfficientNetB5 model is after these models were correctly trained and analyzed using different batch sizes, optimizers, and epochs. With the `Adamax` optimizer and batch size of 32, the EfficientNetB5 produced an accuracy of 94.37%, respectively. Radiologists could use this cost-effective comparative result as a tool or simulator to get a second opinion. Predicting BT as soon as feasible is the main goal of this study. Radiologists may find this comparative analysis model useful as a tool for second opinions. This study contributes to the development of Deep Learning. models by improving diagnosis accuracy.

Declaration

We declare no conflicts of interest and confirm that there was no financial support received for this study.

List of Abbreviations

CNN – Convolutional Neural Networks

MRI – Magnetic Resonance Imaging

T1 – T1 relaxation times of tissues

T2 – T2 relaxation times of tissues

T1 CE – T1-weighted image with contrast enhancement

Efficient Net – Efficient Neural Network

ResNet – Residual Network

VGG – Visual Geometry Group

MobileNetV3 – Mobile Neural Network

DenseNet – Dense Convolutional Network

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