Brain Tumor Classification in Magnetic Resonance Imaging using Convolutional Neural Networks and Transfer Learning*

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Abstract
Brain tumors pose a significant threat with the potential to disrupt critical brain functions and manifest neurological symptoms, warranting the highest concern. The evaluation of these tumors relies on various imaging methods, including Computed Tomography (CT), Magnetic Resonance Imaging (MRI), and ultrasound. Particularly, MRI of the brain is renowned for its capability to provide vital insights into brain structure and tissue irregularities. This study harnesses the transformative influence of technology, notably artificial intelligence (AI) and deep learning (DL), to address this challenge.The novel approach involves the integration of Convolutional Neural Networks (CNNs) with transfer learning from VGG19 and ResNet. The primary objective is the classification of brain tumors into four distinct categories: meningioma, glioma, pituitary adenoma, and cases without tumors. The CNN model in isolation achieves an impressive 97.23% accuracy rate. However, when integrated with VGG19 and ResNet, the accuracy soars to an even higher 98.26%. This innovative amalgamation of technologies holds immense promise for enhancing the precision of brain tumor classification, potentially reshaping the landscape of neuroimaging and healthcare.

Keywords
Brain Tumor, Transfer Learning, Classification, CNNN, VGG19, ResNEt50

1. Introduction

The human brain serves as the central control hub for a multitude of bodily functions, including motor coordination, sensory processing, and vital physiological processes [1]. Any disruption within the brain, such as the emergence of a tumor, has the potential to interfere with its normal operations.

A brain tumor comprises an abnormal cluster of cells within the brain or the cranial cavity. These tumors can vary widely in nature, ranging from benign to potentially life-threatening. They are categorized into primary tumors (originating within the brain) or metastatic tumors (originating elsewhere in the body and spreading to the brain). Treatment approaches for these tumors depend on factors such as type, size, and location. To facilitate discussions related to brain tumors, treatment planning, and prognosis, the World Health Organization [1] has devised a classification and grading system. This system categorizes tumors based on the type of cells they consist of or their primary site of origin [2].

Brain MRI images hold a pivotal role in the detection of tumors and the modeling of their progression, providing essential guidance for treatment decisions. When compared to alternative imaging techniques such as CT scans or ultrasound, MRI scans offer a wealth of comprehensive data, enabling the detailed examination of brain structure and the precise identification of anomalies within brain tissue [3].

The impact of technology, especially artificial intelligence (AI) and deep learning (DL), on the field of medicine is undeniable, and MRI image processing exemplifies this transformation. Deep Learning (DL), with a special focus on Convolutional Neural Networks (CNNs), offers distinct advantages. These include automated feature extraction, heightened accuracy in identifying subtle patterns and irregularities, scalability to handle vast datasets, and the ability to continuously enhance performance through retraining with new data. These attributes position CNNs as powerful tools for the process-

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ing and diagnosis of brain tumors in MRI images [4]. CNNs represent a class of deep learning models specifically tailored for data structured in grids, such as images. They draw inspiration from the visual processing system in the animal brain, allowing them to preserve spatial information while capturing local image features [5]. This method is highly effective, primarily due to its strong feature extraction capabilities [6]. The evolution of CNNs has given rise to various architectural models like Residual Network (ResNet), Network in Network (NiN), VGG, and GoogleNet [7].Transfer learning, a technique that transfers knowledge from one domain to another, has demonstrated its value across diverse domains, applications, and data distributions in both research and training [7]. In this paper, we present a comprehensive approach for classifying brain tumors into four distinct categories: meningioma, glioma, pituitary adenoma, and cases without tumors. Our approach involves the development of a CNN model, followed by training two transfer learning models—VGG19 and ResNet—on the same dataset. The innovation lies in seamlessly integrating these three models into a unified framework, with the primary objective of enhancing the accuracy and precision of brain tumor categorization in MRI scans. This novel technique holds promise as an alternative for more effective MRI diagnosis and treatment planning.

2. Related Work

The process of manually identifying and categorizing brain tumors in large databases of medical images during routine clinical tasks incurs substantial costs in terms of effort and time. Contemporary solutions that leverage Machine Learning (ML) and Deep Learning (DL) methodologies for brain tumor segmentation, detection, and classification [8] have emerged, where they employ Convolutional Neural Network (CNN) architectures for analyzing medical images.

In [9], the authors introduced a method for brain tumor detection using a publicly available brain tumor MRI dataset comprising data from 233 patients. In this approach, a preprocessing step was utilized to enhance the images quality, and two pre-trained deep learning models were used to extract powerful features. The extracted features were then combined into a hybrid vector using the partial least squares (PLS) method. With the aid of agglomerative clustering, the technique achieved 98.95% classification accuracy.

Ramzan et al. [10] directed their efforts toward developing four sequential CNN models for classifying brain tumors in MRI images. These experiments were conducted on a Kaggle dataset comprising 3,000 MRI images. The study involved two key steps: data preprocessing and automatic classification into two classes - tumor and normal - using CNN. The model attained an accuracy of 98.27%.

Hossain et al. [11] proposed a method to extract brain tumors from 2D MRI images using Fuzzy C-Means clustering, traditional classifiers, and a convolutional neural network. The experimental study utilized a benchmark dataset (BraTS) with various tumor characteristics. To differentiate between normal and abnormal pixels based on texture and statistical features, CNN achieved a distinction with an accuracy of 97.87%.

Sultan et al. conducted a study in [12] where they introduced a DL model based on a CNN for classifying various brain tumor types using two publicly available datasets. The initial dataset classified tumors into meningioma, glioma, and pituitary tumors, encompassing 233 cases and comprising a total of 3064 T1-weighted Contrast-Enhanced (CE) images. The second dataset differentiated among three glioma grades (Grade II, Grade III, and Grade IV), involving 73 patients and including 516 T1-weighted Contrast-Enhanced (CE) images. The proposed network structure consists of 16 layers and achieves an accuracy of 96.13% and 98.7% for the two studies, respectively.

Similarly, Nayak et al. [13] introduced a CNN-based dense EfficientNet model with min-max normalization for classifying 3260 T1-weighted contrast-enhanced brain MRI images collected from Kaggle into four categories(glioma, meningioma, pituitary, and no tumor). The experimental results demonstrated performance, with a training accuracy of 99.97% and a testing accuracy of 98.78%.

Khan et al. [14] introduced an automated brain tumor classification system that employs two DL models. The system is designed to classify brain tumors into binary categories (normal and abnormal) using a publicly available CE-MRI dataset consisting of 3064 MRI images. Additionally, it classifies tumors into multiclass categories (meningioma, glioma, and pituitary tumors) using a second dataset containing 152 MRI images collected from the Harvard repository. However, when dealing with limited volumes of data, which is the case in the second dataset, the proposed '23-layer CNN' architecture faced an overfitting problem. To address this issue, they applied transfer learning by combining the VGG16 architecture with the '23-layer CNN' architecture in a reflective manner. The experimental results demonstrate the effectiveness of the proposed models, achieving an accuracy of 97.8% .

In another study, Aurna et al. [15] introduced an accurate and automated brain tumor classification approach using three distinct MRI datasets and a merged dataset. These datasets include images of three types of brain tumors (meningioma, glioma, and pituitary tumors) as well as normal brain images. The study selects the best models and concatenates them in two stages for feature extraction. The most significant features are chosen using Principal Component Analysis (PCA) and fed into

the selected classifier. The proposed ensemble model achieves an average accuracy of 99.13%.
Raza et al. [16] introduced a hybrid deep learning model, named DeepTumorNet, in their study for classifying three types of brain tumors using a basic CNN architecture. The GoogLeNet architecture served as the foundation, with the last 5 layers replaced by 15 new layers in the development of the hybrid DeepTumorNet approach. The proposed model was assessed using the publicly available research dataset, known as the CE-MRI dataset. This dataset consists of 3062 MRI images from 233 patients, representing three distinct types of brain tumors. The evaluation yielded an accuracy of 99.67%.
In [17], Deep learning architectures, including CNN, DNN, LIM (LeNet Inspired Model), AlexNet, and ResNet, were employed to classify brain MRI images as normal or abnormal. Gender and age were considered as additional attributes to enhance the accuracy of the classification. Multiple datasets were utilized, including those from Figshare, Brainweb, and Radiopaedia. The Figshare dataset comprised 1130 abnormal brain MRI images, the Brainweb dataset contained T1 weighted data with 181 slices of normal and abnormal data, and the Radiopaedia dataset included 768 T1 images and FLAIR data. Experimental findings indicated that the LIM model demonstrated superior performance compared to SVM, AlexNet, and ResNet in classifying brain MRI images as normal or abnormal with an accuracy of 82%.
In addition, a segmentation and classification system based on transfer learning is presented in [18]. It uses pretrained CNN (AlexNet and VGG-19) for classification, and threshold and quick bounded box algorithms for segmentation. The evaluation of Kaggle and Figshare datasets showed that the transferred VGG-19 and AlexNet models achieved high accuracies. Specifically, the VGG-19 model obtained 99.75% and 98.50% accuracy, while the AlexNet model achieved 98.89% and 97.25% accuracy, respectively. These findings confirm the superior performance of the VGG-19 model compared to the AlexNet model.
Recently, Gómez-Guzmán et al.[19] utilized the Msoud dataset, which consisted of Figshare, SARTAJ, and Br35H datasets, totaling 7023 MRI images. The dataset comprised four classes: three brain tumor types and healthy brain images. The CNN models, including Generic CNN and six pre-trained models (ResNet50, InceptionV3, InceptionResNetV2, Xception, MobileNetV2, and EfficientNetB0), were trained with preprocessed MRI images using various strategies. Among all the CNN models, InceptionV3 demonstrated superior performance, achieving an average accuracy of 97.12% on this dataset.
Furthermore, Saeedi et al. [20] employed a dataset of 3264 T1-weighted contrast-enhanced MRI brain images, encompassing images of three types of brain tumors and healthy brains. The research commenced with the application of preprocessing and augmentation algorithms to the MRI brain images. Subsequently, a 2D CNN and a convolutional auto-encoder network were developed and trained with predetermined hyperparameters. The 2D CNN featured several convolutional layers, with all layers in this hierarchical network utilizing a 2*2 kernel function. Additionally, six machine-learning techniques were employed and compared for brain tumor classification. The obtained results indicated a training accuracy of 96.47% for the proposed 2D CNN and 95.63% for the proposed auto-encoder network.

3. Proposed Methodology

In our suggested approach, we propose using a pair of models to classify brain tumors into four categories: Pituitary, Meningioma, Glioma, and No Tumor. The initial model utilizes a Simple CNN, while the second model improves precision by incorporating transfer learning from pre-trained VGG19 and ResNet50 models.

3.1. Proposed Methodology of Tumor Classification Using CNN

Convolutional Neural Networks (CNNs) are essential for improving the accuracy of tumor identification in medical image processing. Our goal is to develop a model that accurately detects tumors from two-dimensional brain MRI data. CNNs are preferred over fully-connected neural networks for tumor detection due to their effective parameter sharing and sparse connectivity, which maximize accuracy and computational efficiency by utilizing features found in medical images.

We have integrated and implemented 6 CNN layers specifically designed for tumor detection and classification, as illustrated in Figure 1. This combined model, comprising 8 stages and involving the integration of hidden layers, has demonstrated the most remarkable outcomes in the context of tumor identification. In the following paragraph, we provide an overview of the suggested technique and a brief explanation of each of its components.

Starting with a convolutional layer as the initial step, the input of MRI images is shaped into a uniform dimension of 224x224x3, ensuring consistency across all images. Once the images are standardized, a convolutional kernel is constructed to interact with the input layer. This kernel employs 32 convolutional filters, each with a size of 3x3, and operates on 3-channel tensors. The purpose is to extract low-level features from the MRI data efficiently without overparameterizing, considering the complexity and quantity of the data. We specifically use the Rectified Linear Unit (ReLU) activation function to introduce non-

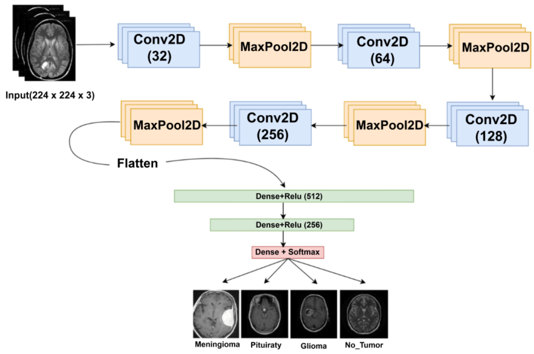

Figure 1: Proposed CNN model architecture.

linearity and prevent it from aligning too closely with the output.

The ConvNet architecture undergoes a systematic reduction in spatial dimensions, effectively reducing parameter count and computational load. A valuable Max Pooling layer is adept at curbing overfitting concerns tied to brain MRI images. For geographical data that complements input images, MaxPooling2D is employed. A pivotal convolutional layer operates at dimensions of 111x111x32. The pooling size of (2, 2) enacts vertical and horizontal downsizing due to input image segmentation across both spatial dimensions.

The network comprises multiple convolutional blocks, progressively increasing filter count to 64, 128, and 256 in subsequent layers. This strategic augmentation aims to capture intricate features in the input MRI images. Interspersed Max Pooling layers mitigate overfitting concerns. The architecture concludes with a spatial dimension of 7x7x256, signaling an abstract representation for downstream tasks. This design fosters computational efficiency and addresses standardization concerns for diverse MRI inputs, underscoring a commitment to non-linearity and prevention of overfitting in the network's learned representations.

After the pooling layer, we obtain a pooled feature map. Flattening becomes crucial at this point, as it requires us to reshape the entire matrix that represents the input images into a single-column vector. This modification is necessary for further processing. We then feed this flattened vector into the Neural Network for additional processing.

In our methodology, we incorporate three dense layers: the first layer comprises 512 hidden units, the second layer consists of 256 hidden units, and the third layer serves as the final layer. This sequence of 512, 256, and 4 is tailored to match the complexity of our classification task. To address potential overfitting risks, we introduce a dropout rate of 50% between these hidden layers. For our multiclass (4 classes) classification task, we opt for the softmax activation function in the final layer, as it consistently demonstrates superior accuracy compared to other options. We also employ the "categorical cross-entropy" loss function. Our optimization approach of choice is "Adam", an abbreviation for "Adaptive Moment Estimation". Adam builds upon the foundations of gradient descent and integrates concepts from the Adaptive Gradient Algorithm (Adagrad) version. It adapts step sizes for each parameter dynamically during the training process using a decaying average of partial gradients. The model underwent training for 32 epochs. However, in the current context, the accuracy falls short of our expectations. Consequently, we have decided to enhance our approach by incorporating transfer learning through ResNet50 and VGG19 architectures. The objective is to fortify the accuracy of our model and further elevate its overall performance.

3.2. Proposed Methodology Using transfer learning

Within this section, we have utilized two separate models – VGG-19 and ResNet-50 – to tackle the complexities associated with brain tumor detection and classification. We will provide detailed explanations of these two models in the subsequent sections.

3.2.1. VGG-19

The VGG network, created by Simonyan and Zisserman at the University of Oxford in 2014 [21], is a widely recognized pre-trained CNN model. Trained on the extensive ImageNet ILSVRC dataset containing 1.3 million images divided into 1000 classes, it consists of 19 layers, including 16 for convolutions, 3 fully connected layers, and 5 for pooling. Instead of average pooling, Maxpooling is used for downsampling. The fully connected layers consist of two sets, each with 4096 channels, followed by another fully connected layer with 1000 channels for label prediction. Importantly, the last fully connected layer benefits from GPU acceleration during training, enabling the use of a softmax layer for classification.

3.2.2. ResNet-50

ResNet-50, an abbreviation for residual neural network, is a convolutional neural network featuring a depth of 50 layers. This model was developed and trained by He et al. [22] in their research conducted in 2016. Similar to VGG-19, this model is able to classify a wide range of objects, with a total of 1000 categories. The model's training regime capitalized on a dataset comprising more than 1 million images sourced from the ImageNet database.

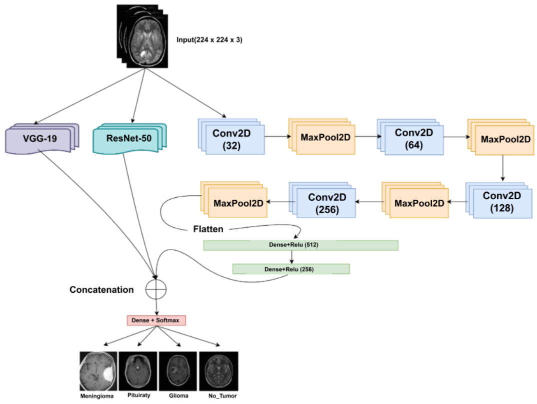

Figure 2: Applying Transfer Learning in CNN Architecture.

These images were 224x224 pixels in color. Residual networks of varying depths, including ResNet-50, ResNet-101, and ResNet-152, have demonstrated enhanced accuracy in image recognition tasks, contributing to advancements in the field.

3.2.3. Proposed CNN Architecture using Transfer Learning

Transfer learning plays a crucial role in augmenting the base CNN model, utilizing the feature maps generated by the pre-trained VGG19 and ResNet50 models. Both VGG19 and ResNet50 models undergo weight fetching, retaining the original weights acquired during the initial training. Specifically, only the last four layers introduced in the subsequent training session remain trainable. This strategic approach ensures the preservation of pre-existing knowledge from the initial training, with fine-tuning focused on the recently added layers for optimized performance in targeted classification tasks. On the flip side, we loaded pre-existing saved files from the pre-trained models (VGG19 and RESNET50 Model). Subsequently, we concatenated these models with the proposed CNN Model to create a new model named "Concatenated Model", that generates output by averaging predictions from the three individual models. This ensemble technique is designed to improve overall prediction performance by capitalizing on the diverse strengths of each base model. This contributes to heightened robustness and generalization capabilities across a range of data types. Figure 2 presents a comprehensive illustration of the model.

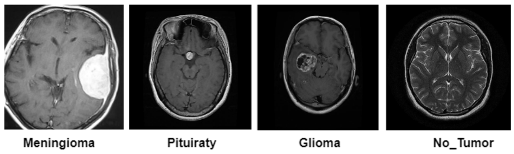

Figure 3: Examples of Brain Tumor Dataset Classes.

4. Experimental Results

To validate our proposed model, we illustrate the steps involved in detecting and classifying brain tumors from 2D Brain MRI images and provide a comparative analysis of our classification models using deep learning. Our results indicate an accuracy of 97.23% with the CNN model and an even higher accuracy of 98.26% when employing a combination of CNN with VGG19 and ResNet50.

4.1. Experimental Dataset

In our exploration of brain tumor detection, we extensively leveraged various brain MRI image databases to construct a comprehensive dataset for the training, validation, and testing phases of our Convolutional Neural Network (CNN) models. The dataset utilized is curated from the Br35H dataset and the Chen Jung dataset [23]. It's important to note that the Chen Jung dataset comprises three tumor classes (glioma, meningioma, pituitary), whereas the class without a tumor was sourced from the Br35H dataset. The latter dataset originally contains only two classes (tumor, non-tumor). We specifically extracted the non-tumor class after preprocessing and analysis to seamlessly integrate it with Cheng Jun's dataset. This meticulous curation ensures a comprehensive and diverse representation of brain MRI images for our research.

The dataset used for training and testing our models consists of around 3027 T1-weighted MRI images in JPEG format.These images were thoughtfully classified into four distinct classes: glioma, meningioma, pituitary, and no tumor. The following Figure 3 illustrates examples from each class.

We partitioned the dataset into three subsets: training, validation, and testing, with respective percentages of 80%, 10%, and 10%. However, the initial image count proved insufficient for effective neural network training. To address this limitation, we implemented a practical solution: data augmentation. This image-processing technique enabled us to generate additional data and images from the original dataset. In the training phase, the initial count of 2419 images was augmented, resulting in a total of 4838 images.

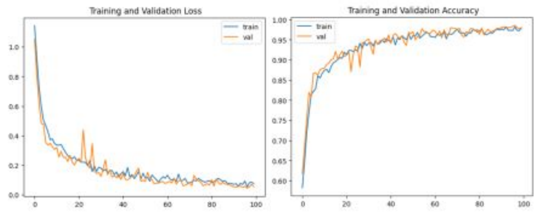

Figure 4: Chart depicting Training and Validation Model Accuracy and Loss utilizing the CNN Model

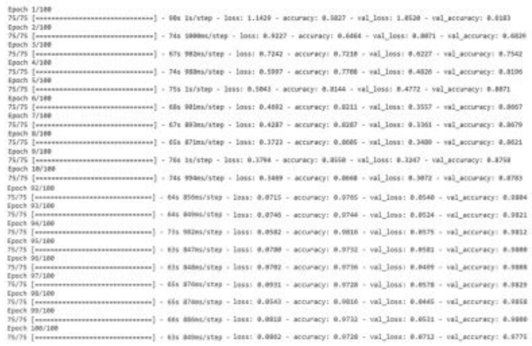

Figure 5: Final output of the CNN Model

4.2. Evaluation metrics

The algorithm's performance measures, including accuracy, were assessed using equation-defined TP (true positive), TN (true negative), FP (false positive), and FN (false negative) values.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

- TP : corresponds to cases where both the predicted and actual cases were correctly identified as tumors.
- TN : corresponds to cases where both were correctly identified as normal.
- FP : corresponds to cases where the predicted case was identified as a tumor, but the actual case was normal.
- FN : corresponds to cases where the predicted case was identified as normal, but the actual case was a tumor.

4.3. Discussions and comparisons

Various experimental assessments were conducted to validate the proposed dense CNN model. All experiments were performed in a Python programming environment with GPU support. Initially, image preprocessing involved augmenting the images for training, enhancing the model's accuracy in detecting augmented tumors. The proposed model achieved an accuracy of 97.23% on the training dataset and 97.75% on the validation dataset, as illustrated in Figures 4 and 5.

The experiments were conducted over 100 epochs, with a batch size of 32 and image size set at (224x224x3). In terms of accuracy, the initial validation accuracy started below 61% but rapidly increased to nearly 68% after the first epoch. Similarly, the initial validation loss was above 1.05 but decreased to below 0.80 after the first epoch. Figure 5 depicts the positive trend in improving accuracy and reducing loss. The validation accuracy, initially low, progressively improved to almost 97.23%. The subsequent experiments involved the ResNet50 model, VGG19, and a concatenation of all three models, as demonstrated in Figures 6, 7, and 8, respectively.

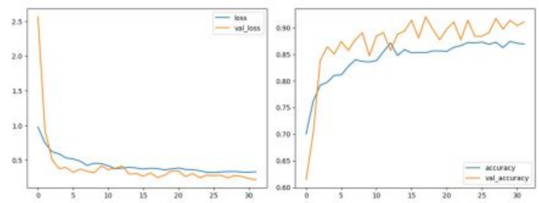

Figure 6: Chart depicting Training and Validation Model Accuracy and Loss utilizing the ResNet50 Model

Figure 6 illustrates the training process of the ResNet model, encompassing 32 epochs, and utilizing an image size of (224x224x3). Regarding accuracy, the initial validation accuracy commenced below 69%, exhibiting a swift rise to nearly 77% after the inaugural epoch. Similarly, the initial validation loss surpassed 1.01 but diminished to below 0.69 following the first epoch. Figure 6 visually captures favorable accuracy enhancement and loss reduction. Notably, the validation accuracy, initially modest, exhibited progressive improvement, reaching 88.7%.

Similarly, the VGG19 model underwent training for 32 epochs, utilizing an image size of (224x224x3). Concerning accuracy, the initial training accuracy commenced below 76%, experiencing an increase to nearly 85% after the first epoch. Similarly, the initial training loss exceeded 0.74 but decreased to below 0.49 following the first epoch. Figure 7 illustrates the positive trend of enhancing accuracy and reducing loss. The validation accuracy, initially modest, exhibited progressive improvement, reaching almost 94.58%.

Finally, Figure 8 illustrates the positive trend in improving accuracy and reducing loss of the concatenated model involving the three architectures: VGG19, ResNet 50, and a simple CNN model trained on the same dataset, concatenated together. This model underwent training

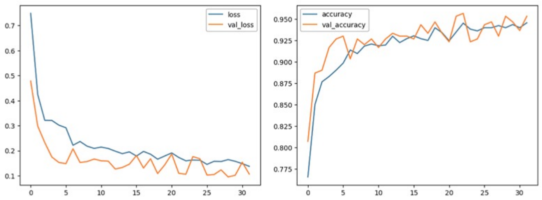

Figure 7: Chart depicting Training and Validation Model Accuracy and Loss utilizing the VGG19 Model

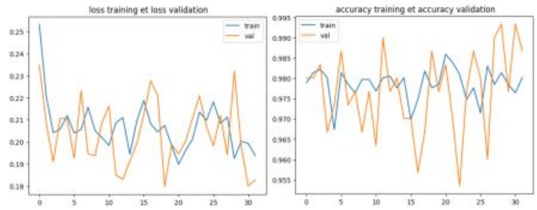

Figure 8: Chart depicting the Training and Validation Model Accuracy and Loss with the Concatenated Model

for 32 epochs, with a batch size of 32 and an image size set at (224x224x3). In terms of accuracy, the initial training accuracy started below 96%, experiencing an increase to nearly 97% after the first epoch. Similarly, the initial training loss exceeded 0.25 but decreased to below 0.22 following the first epoch. After completing the last epoch, the training accuracy reached 98.37%, with a validation accuracy of 99.34%.

The CNN model achieves a testing accuracy of 98.69% with a testing loss of 0.13. In comparison, the VGG19 model attains a testing accuracy of 95.76% and a testing loss of 0.10. The ResNet50 model demonstrates a testing accuracy of 96.94% with a testing loss of 0.1339. Remarkably, when concatenating the three models (CNN, VGG19, and ResNet50), an outstanding testing accuracy of 99.34% is achieved, accompanied by a test loss of 0.17. A detailed comparison of test accuracy and loss among different models is presented in Table 1

Table 1
Comparison of accuracy and loss among different pre-trained deep-learning-based techniques.

Model	Dataset	Testing Loss	Testing Accuracy
Propose CNN Model	T1-weighted dataset	0.13	98.69%
VGG19	T1-weighted dataset	0.10	95.76%
ResNet 50	T1-weighted dataset	0.26	89.90%
Concatenating Architecture	T1-weighted dataset	0.17	99.34%

The proposed model's accuracy is evaluated in comparison with other developed models designed for brain tumor classification. These models are assessed across three types of classifications: the binary classification of 02 classes (normal or abnormal brain), the classification of 03 classes encompassing the three types of brain tumors (Meningioma, Glioma, Pituitary), and the 04-class classification used in our studies, which includes the three types of brain tumors along with a class denoted as "no Tumor." Various datasets are employed for this comparative analysis. Table 2 presents the accuracy achieved by each model, with accuracies ranging from 82% to 98.78%. Notably, all these values fall below the accuracy attained by our model, which stands at 99.34%.

5. Conclusion

Numerous techniques have been explored in the field of brain tumor detection, and some studies have demonstrated the effectiveness of applying transfer learning to medical data, including MRI images. This very motivation guided our research endeavors. After the rigorous training and evaluation of the four models, we achieved remarkable results.

The results from each model strongly highlight the efficacy of combining the three models: the Proposed CNN model, VGG19, and ResNet. During the validation phase, this amalgamated model achieved an impressive accuracy of 98.26%, outperforming the Proposed CNN model's accuracy of 97.23% when used individually. These findings consistently emphasize the high accuracy attainable through the fusion of these three models, reinforcing the potential of transfer learning in the realm of medical data recognition. Looking ahead, our research will broaden its horizons. We plan to enrich the dataset by incorporating a more extensive collection of images and labels. This expansion will serve to assess the model's ability to maintain its effectiveness across a broader spectrum of medical images.

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Table 2
Comparison of accuracy and loss among different pre-trained deep-learning-based techniques.

Method	Dataset	Tumor Classes	Techniques Used	Accuracy
Cheng, Jun, et al.[24]	Br35H Dataset	03 classes	closed-from metric learning algorithm (CFML)	94.68%
Nayak et al. [13]	T1-weighted contrast-enhanced MRI images	04 classes	EfficientNet CNN	98.78%
Sultan et al.[12]	T1-weighted Contrast-Enhanced (CE)	03 classes	16-layer CNN	96.13%
Wahlang et al.[17]	Multiple datasets (Figshare, Brainweb, and Radiopaedia	02 classes	LIM model	82%
Proposed method	T1-weighted dataset	04 classes	CNN + Transfer Learning (VGG19, ResNet50)	**99.34%**

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