Improving Detection and Classification Of Brain Tumors Using DenseNet201

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Abstract— Brain tumors are among the leading causes of death worldwide. A brain tumor may originate in the brain or develop elsewhere in the body and metastasize to the brain, leading to secondary brain tumors. Thus, brain tumors can take many different forms. In this study, brain tumors were detected and classified based on magnetic resonance imaging (MRI) involving three different types of brain tumors and non-tumors. VGG-16, VGG-19 (Visual Geometry Group), DenseNet201 (Densely Connected Convolutional Networks), Inceptionv3, ResNet-50 (Residual Network with 50 layers), and EfficientNet-B0 were among the convolutional neural network (CNN) models that were employed and analyzed in order to determine the optimal model for detecting and classifying brain cancers. The best model was DenseNet201, which achieved accuracy, precision, and recall of 99.31%, 99.31%, and 99.25%, respectively.

Keywords— Brain Tumors , Magnetic resonance imaging, VGG-19, Densenet201, Inceptionv3, Resnet-50, EfficientNet-B0.Introduction

I. INTRODUCTION

One of the most difficult cancers to identify and treat is a brain tumor. They vary in size, shape, and aggression and can arise in various brain regions. Accurate brain tumor categorization and early diagnosis are essential for successful therapy and better patient outcomes. Traditional methods of detecting and diagnosing brain tumors, such as biopsy and histological analysis, can be invasive, time-consuming, and may have limited accuracy [1-2]. As a result, there is increasing interest in using machine learning (ML) methods for medical imaging-based brain tumor diagnosis and classification. Resolving diagnostic problems is greatly aided by the medical imaging technique used to diagnose brain tumors [3, 4, 5]. MRI and computed tomography (CT) are useful techniques for revealing crucial details regarding the existence and extent of aberrant brain tissue. Since MRI uses safe radiation to produce detailed images of the brain's internal structures, it is preferred over CT scans, which use dangerous radiation [6, 7]. The ability of machine learning (ML) systems to identify brain tumors early from MR images has been shown in a number of studies [8-10]. One of the most popular machine learning methods for classifying brain tumors is deep learning (DL) [10]. CNNs are among the most widely utilized deep learning algorithms, particularly in applications related to medical imaging [12-15].
CNNs can help in the automatic analysis of big MRI image collections, enabling precise classification and early brain tumor detection. Through the analysis of extensive datasets of MRI images, they can also spot distinctive features and patterns that differentiate between various kinds of brain cancers.
The six CNN architecture models used in this study (VGG-16, VGG-19, DenseNet201, InceptionV3, ResNet-50, and EfficientNet-B0) were trained to detect and classify three distinct kinds of brain tumors as well as MRI-obtained non-tumor pictures (glioma, meningioma, and pituitary).

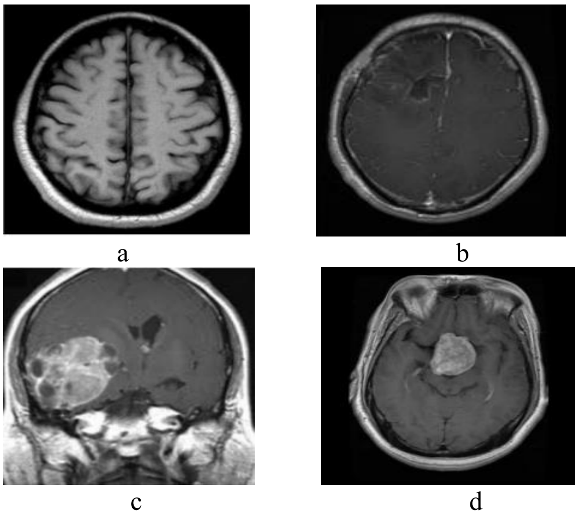

Figure 1: Non-tumorous and three types of brain tumors: a) Normal, b) Glioma, c) Meningioma, d) Pituitary

II. Literature Review

Recently, many techniques are being studied, and research into identifying and classifying brain tumors using MRI scans has progressed significantly. In this section, previous studies on the detection and classification of brain tumors will be reviewed, with a focus on those that employed DL techniques.

Francisco Javier Díaz-Pernas et al. [16] developed a multiscale CNN-based brain tumor segmentation and classification model that obtained a 97.3% accuracy rate for three distinct tumor types: pituitary, glioma, and meningioma. In Ref. [17], presented a DL technique that extracted features from brain MR images using a GoogLeNet model. They had a 98% accuracy rate for the same three kinds of brain tumors. A. Priya and V. Vasudevan [18] used a hybrid model involving AlexNet and GRU neural networks to identify and classify brain cancers from MRI data with a 97% accuracy rate. The BTC-f CNN model was proposed in Ref. [19] to classify three types of brain cancers (pituitary tumor, meningioma, and glioma) with a 98.86% accuracy rate.

In Ref. [20], ResNet (2+1)D and ResNet mixed convolution models were used to classify different types of brain tumors, with ResNet mixed convolution reaching a test accuracy of 96.98%.

Wen Jun & Zheng Liyuan [21] used a dataset of 3064 MR images to develop a brain tumor classification model that incorporates a multipath network and attention mechanism, achieving an accuracy of 98.61%. MuSunil Kumar & Dilip Kumar [22] classified three different kinds of brain cancers (glioma, meningioma, and adenoma) using a CNN model with the Adam optimizer had the best accuracy, 86.23%.

Ramin Ranjbarzadeh et al. [23] used CNN to detect cancer within a specific region of an image and achieved different accuracy during the image processing process with an average Dice score of 92% for the whole tumor, 91.1% for tumor enhancement, and 87.2% for tumor core segmentation.

Ramdas Vankduthoo and Mohamed Abdel Hamid [24] suggested using CNN to identify various types of cancerous and non-cancerous brain tumors and the accuracy of this classification reached 95.17%.

Kakarla J, Isunuri BV, et al. [25] suggested an eight-layer CNN brain tumor classifier that had a 97.42% accuracy rate.

Irsheidat, S., and Duwairi [26] utilized a CNN model to predict brain cancers from MR images, and achieved an accuracy of 96.7% on the evaluation data.

Ali Ari and Davut Hanbay [27] proposed a three-stage approach consisting of preprocessing, tumor classification, and tumor region extraction and obtained an accuracy of 97.18%.

Md Ishtyaq Mahmud, et al. [28] utilized CNN network to classify brain cancers and the model achieved an accuracy of 93.3%.

Obeidavi et al. [29] used the BRATS 2015 MRI dataset to create a CNN-based residual network for brain tumor detection. Their model is reportedly 97.05% accurate.

Hareem Kibriya et al. [30] suggested a CNN for classifying brain tumors based on a dataset of 3064 MRI images. where the accuracy of the study was 97.2%.

Vinayak K. Bairagi et al. [31] suggested CNN architecture to automatically detect brain tumors based on MR images. Several CNN architectures were explored and 98.67% accuracy was achieved using CNN AlexNet.

III. Methodology

As illustrated in Figure 2, the methodology utilized in this paper comprised five steps: data collection, preprocessing, dividing the dataset into training and test sets, model training, and model evaluation.

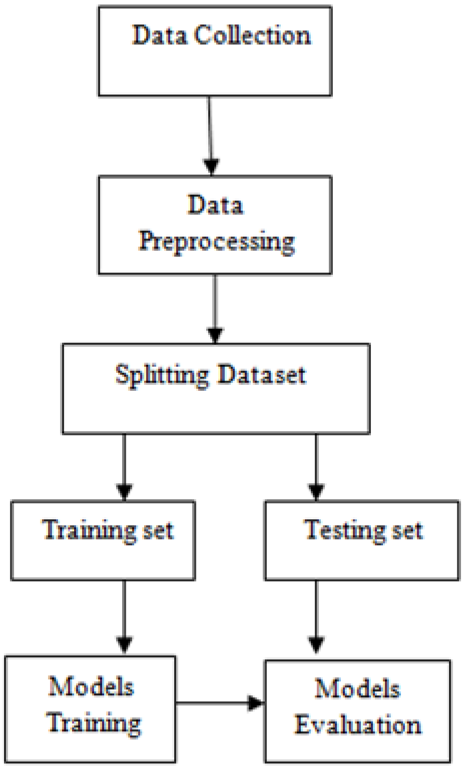

Figure 2 Steps of the proposed model for brain tumors detection and classification.

A. Data Collection

This step involved the collection of 7,023 MRI brain images, including 1,757 images of pituitary tumors, 1,645 photos of meningiomas, 1,621 images of gliomas, and 2,000 images of non-tumorous instances (Figure 3).

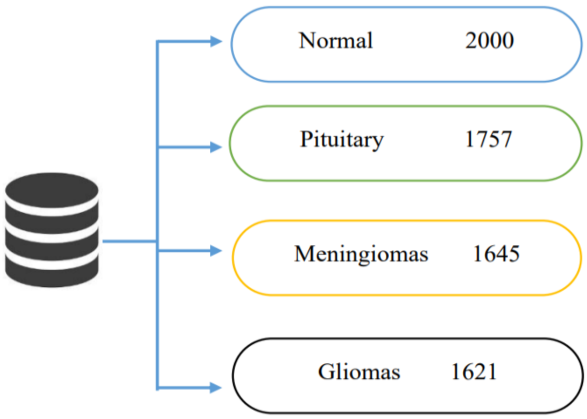

Figure 3: Collected Dataset

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B. Data Pre-processing

The collected MRI scans must be preprocessed to remove any noise and other image distortions that could potentially impact the accuracy of the CNN algorithms.

C. Splitting Dataset

As illustrated in Figure 4, the research dataset was split into two sections: 80% (60% for training, 20% for validation) and 20% for testing.

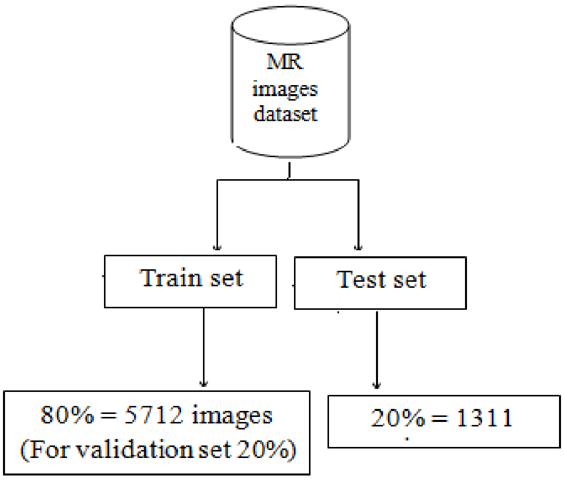


Figure 4: Dataset splitting

D. Models Training:

CNN models have been developed and compared for the purpose of detecting and classifying brain tumors in order to choose the most accurate model. As seen in Figure 5, convolutional, pooling, and fully linked layers are commonly seen in CNN architectural designs.

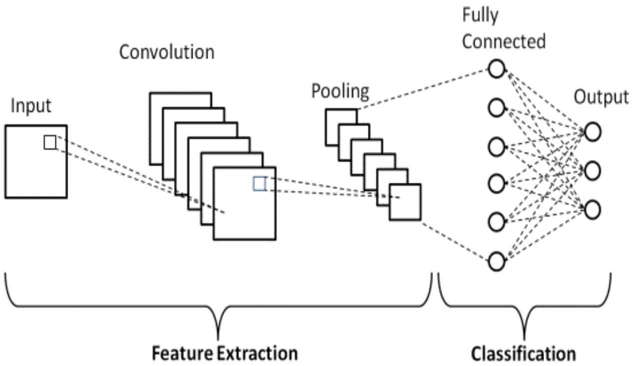


Figure 5: CNN Architecture

Six CNN models, including ResNet-50, VGG-16, VGG-19, DenseNet-201, InceptionV3, and EfficientNet-B0, were utilized to determine the best model. A brief explanation of these models is provided below:

ResNet50

The ResNet-50 model has 50 levels of depth. By avoiding some intermediary levels, the skip connection creates a residual block that links a layer's activations to later layers (Figure 6).

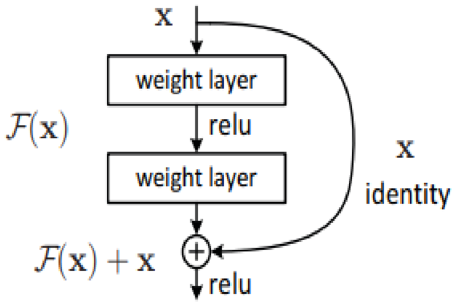


Figure 6: Residual learning: a building block.

VGG

VGG is a traditional CNN design that was created using an examination of growing network depth. The VGG-16 model has sixteen layers, comprising thirteen convolutional layers and three fully connected layers.

However, the VGG-19 model has a 19-layer network topology. However, the VGG19 model has a 19-layer network topology with 16 convolutional layers and 3 fully linked layers. In comparison to VGG-16, VGG-19 contains three extra convolutional layers.

DenseNet201

A CNN type known as a DenseNet makes use of dense blocks to create dense connections between layers, which let each layer access feature information from all layers that came before it. Every layer passes on its own feature maps to every layer after, it while also receiving new inputs from all layers before it in order to preserve the feed-forward nature.

InceptionV3

InceptionV3 is a CNN architecture that consists of convolutions, fully linked layers, concatenations, dropouts, average pooling, and max pooling. To compute the loss, Softmax is employed.

The EfficientNet B0

EfficientNet is a type of CNNs. The fundamental concept underlying Efficient Net is a novel scaling strategy that uses sophisticated coefficient scaling to scale models in a straightforward yet efficient manner while uniformly measuring all depth, width, and resolution variables.

E. Models Evaluation

The testing sets are used to assess the performance, accuracy, and generalization capacities of the trained models. After that, the model with the best performance is chosen for deployment.

IV. Result and Discussion

Results from the application of the suggested model are shown in this section. Three metrics (accuracy, recall, and precision) are used to illustrate the performance outcomes of the suggested models in Figure 7, where the performance of the DenseNet-201 model was shown with the highest accuracy of 99.31%.

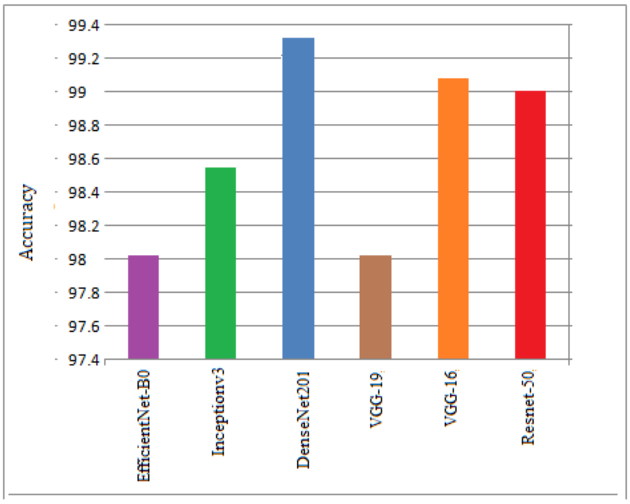


Figure 7: The accuracy of each model.

The confusion matrices for the DenseNet-201 model and the other models are displayed in Figure (8) and Figure (9), respectively.

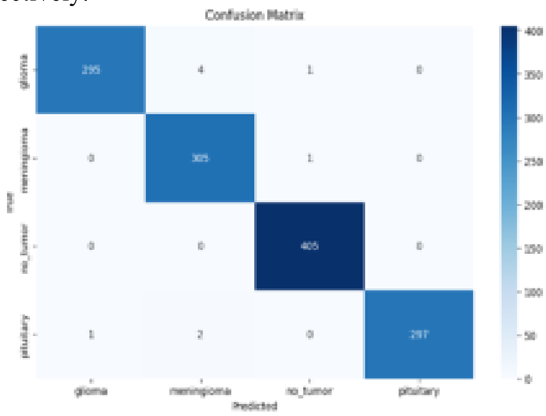
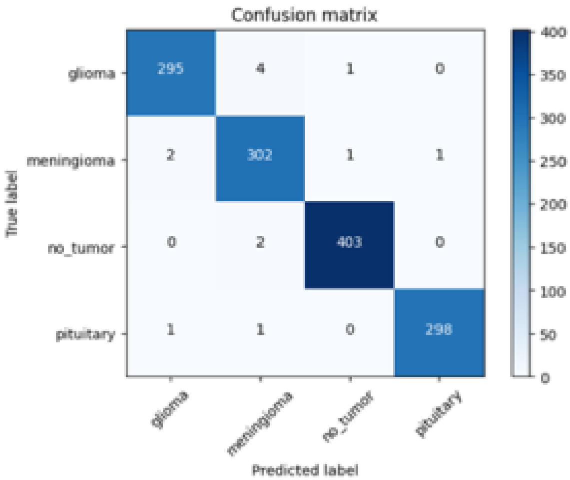
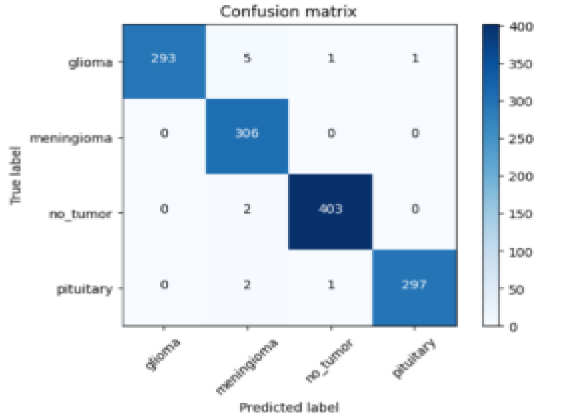


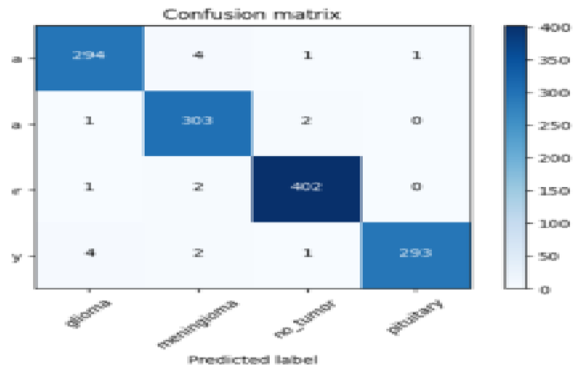
Figure 8: Confusion matrix of the DenseNet201 model.



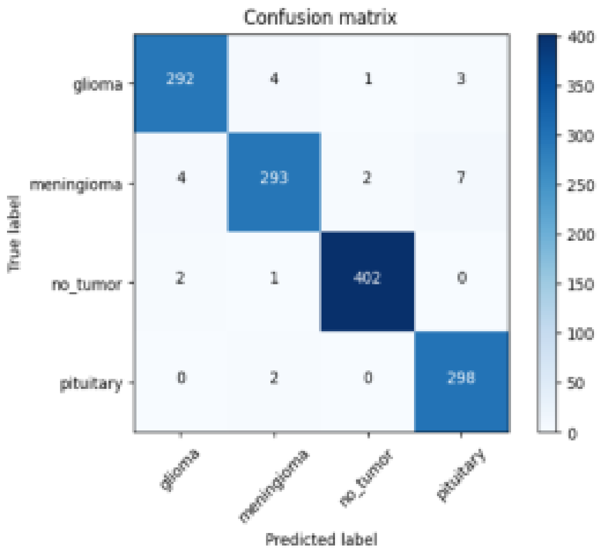
(a)



(b)



c)



d)

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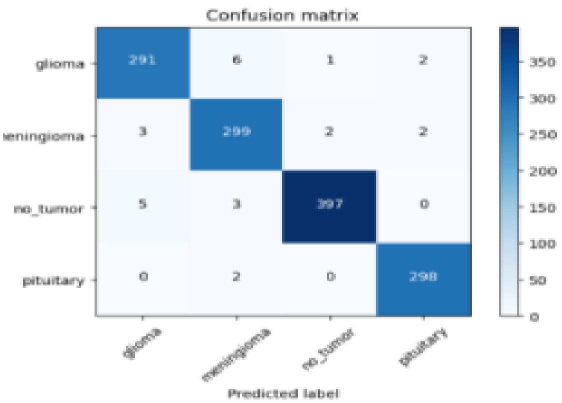

e)
Figure 9: Confusion Matrix
a) ResNet50, b) VGG16, c) InceptionV3, d) Efficient_B0
e) VGG19

Table 1 shows the average precision and recall of the DenseNet-201 model, which are 99.31% and 99.25%, respectively.

Table 1. The performance of DenseNet201 model.

Category	Precision (%)	Recall (%)
Non-tumorous	99.78	99.79
Glioma	99.71	98.19
Meningioma	98.14	99.91
Pituitary	99.62	99.12
Average	**99.31**	**99.25**

The DenseNet201 model's accuracy and loss curves are displayed in Figures 10-11. The lowest error rate, which happened in epoch 11, was 0.038.

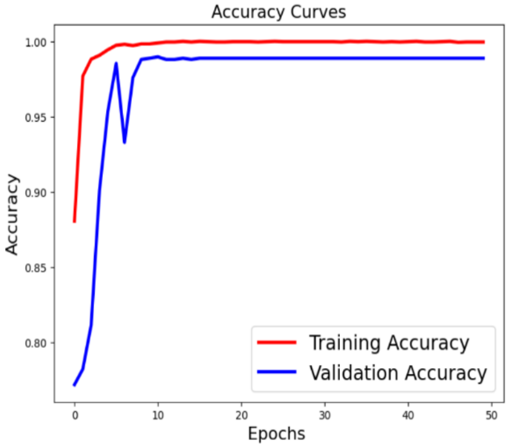

Figure 10: Accuracy Curves

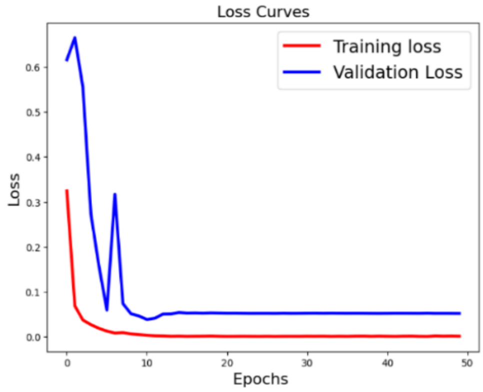

Figure 11: Loss Curves

Our DenseNet201-based method achieves a classification accuracy of 99.31%, surpassing previous approaches such as multiscale CNN (97.3% [16]), GoogLeNet (98% [17]), AlexNet-GRU hybrid (97% [18]), and BTC-fCNN (98.86% [19]), as detailed in Table 2. This superior performance can be attributed to DenseNet201's architectural features: dense connectivity that enhances feature reuse and mitigates vanishing gradients, more effective parameter utilization, and improved learning of complex hierarchical tumor features through deep supervision. Clinically, the accuracy enhancement of approximately 1.31–2.31% has the potential to reduce diagnostic errors in tumor identification and classification. Methodologically, the robustness of our results is supported by a thorough evaluation across six different CNN architectures, validation on a larger and more diverse dataset comprising 7,023 images from four classes, and detailed performance reporting, including high precision (99.31%) and recall (99.25%) metrics.

Table 2. Performance comparison with previous studies

Study	Method	Accuracy
[16]	Multiscale CNN	97.3%
[17]	GoogLeNet	98%
[18]	AlexNet-GRU	97%
[19]	BTC-fCNN	98.86%
Our work	**DenseNet201**	**99.31%**

V. Conclusion

Early detection and classification are essential for the successful treatment of brain cancers.
The most advanced networks for identifying and categorizing brain tumors are CNNs, which offer higher accuracy.

This study utilizes CNN models with six different architectures (VGG-16, VGG-19, DenseNet-201, InceptionV3, ResNet-50, and EfficientNet-B0) to classify brain tumors from MRI images.

The dataset comprises 7023 MRI brain images, including 2000 non-tumorous images, 1757 pituitary images, 1645 meningioma images, and 1621 glioma images.

While these results are promising, we acknowledge the need for future multi-center validation studies to assess generalizability across different MRI protocols and patient populations.

According to this study, the DenseNet-201 model performed the best, showing accuracy, precision, and recall of 99.31%, 99.31%, and 99.25%, respectively.

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