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# Brain Tumor Classification using Convolutional Neural Network

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## Abstract

This study intuitively addresses a crucial need in the medical domain by introducing a customized Mobile-Net model for classifying brain cancer in medical imaging data. The paramount importance of accurate classification in cancer diagnosis and treatment planning cannot be emphasized further. This particular research primarily focuses on the practical application of semantic classification techniques to precisely identify and outline brain cancer zones in medical imaging data. By utilizing a Mobile-Net architecture, the developed model highlights outstanding performance with an accuracy score of 85%.

**Keywords:** Deep Convolutional Neural Network, Python, Google Colab, Medical Image Analysis, Deep Learning.

## 1. Introduction

In these research studies, high accuracy has been demonstrated in the categorization of brain tumors across different categories, like normal, meningioma, glioma, metastatic, pituitary, and a variety of tumor grades. The CNN models have been extensively trained and tested on massive datasets of brain MRI images and they have shown promising results in accurately identifying and classifying brain tumors. The utilization of deep learning models, such as CNNs, has obliterated the need for hand-crafted feature extraction methods, leading to


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enhanced accuracy and reduced computation time. The proposed models have attained high prediction accuracy, ranging from 84% to 100%, for binary and multiclass brain tumor categorization. Brain tumors are categorized into two varied types: low-grade (grade 1 and grade 2) and high-grade (grade 3 and grade 4) tumors. The combination of CNN and other techniques, like Graph Convolutional Networks (GCN), has been proposed to additionally enhance the accuracy of brain tumor classification. The research studies have also highlighted the importance of early and precise detection of brain tumors for proper treatment and better survival rates. The proposed CNN models and their experimental results are now publicly accessible for further research and development. These research studies have demonstrated the effectiveness of CNNs in precisely classifying brain tumors across different categories, and the proposed models have frequently showcased high prediction accuracy, ranging from 84% to 100%, for binary and multiclass brain tumor classification.

The combination of CNN and other techniques, like Graph Convolutional Networks. (GCN), is recommended to further enhance the accuracy of brain tumor classification. The proposed CNN models and their experimental results are now publicly available for additional research and development. Brain tumor classification using Convolutional Neural Networks (CNNs) has surfaced as a potent and accurate method for identifying and categorizing various types of brain tumors. Researchers have devised CNN-based models that can categorize brain tumors across numerous categories, like normal, meningioma, glioma, metastatic, and pituitary tumors, with high accuracy rates. The BCM-CNN (Brain Tumor Classification Model based on CNN) stands as an epitome of an advanced model that utilizes a 3D CNN structure and accomplishes high accuracy in brain tumor classification. Other strategies, like the Hybrid KFCM (K-Fuzzy C-Means) methodology, integrates CNNs along with graph convolutional networks (GCNs) to enhance the classification of brain tumors. CNN-based models boast several advantages over traditional machine learning methods, such as SVM and KNN, because they do not necessitate handcrafted feature extraction and can directly learn attributes from the input images. These result in lower complexity and higher accuracy. The CNN-based brain tumor classification models aspire to improve the accuracy and efficiency of diagnosing brain tumors, which is pivotal for proper treatment and better survival rates. An MRI image divulges more information about the given medical image than a CT or ultrasound image.

## 2. Literature Review

Several studies have explored the use of deep learning techniques to classify brain tumors. These studies demonstrated the effectiveness of various deep learning models, such as convolutional neural networks (CNNs), in accurately classifying different types of brain tumors using MRI data. For example, one study proposed using a deep CNN model to classify brain tumors and achieved a high accuracy of 99.90% by using transfer learning and data augmentation techniques. Another study developed a hybrid deep learning model that outperformed existing algorithms, achieving 99.7% classification accuracy, and the feasibility of its use in clinical practice has been demonstrated. Deep learning techniques, especially CNNs, are used to accurately classify brain tumors using MRI data. Furthermore, the concept of deep transfer learning has been employed in one study to extract features from brain MRI images for tumor classification using pre-trained Google Net.

Multiscale modeling for image analysis in brain tumor research combines cancer simulation and medical image processing methods to model tumor growth and establish correlations between healthy brain images and images of diseased patients. This is done using multiscale models that include growth simulation from the cellular to the biomechanical level, taking into account cell proliferation and tissue deformation. Large-scale deformations are handled using an Eulerian approach to finite element calculations that can act directly on the image voxel mesh. Non-rigid registration is then used to create a close match between the modified atlas and the patient image.

The use of multifractal texture estimation for brain tumor detection and segmentation has been explored in various research papers. One particular study introduced a probabilistic model to characterize tumor tissue in brain magnetic resonance (MR) images, assessing its effectiveness in patient-independent brain tumor tissue feature extraction and tumor segmentation. Specifically, in this study, we employed a multiresolution fractal model called multifractal Brownian motion (MBM) to describe the texture of brain tumors. We developed a brain tumor segmentation method based on multifractal features and demonstrated the technique's effectiveness through experimental results obtained from 14 patients, involving 309 MRI slices.

## 2.1 Tumor-Cut

The segmentation of brain tumors on contrast-enhanced MR images for radiosurgery shows that the segmentation of brain tumors is an important task in medical diagnosis and treatment planning. Challenges associated with segmentation include image noise, low contrast, intensity shift, and tissue type variations. Automatic or semi-automatic segmentation methods supported by artificial intelligence are essential for accurate diagnosis and treatment planning. Deep learning methods such as deep neural networks have shown promising results in brain tumor segmentation, with Dice similarity coefficients of 0.88, 0.83, and 0.77 for the entire region, core region, and extension region, respectively. Artificial intelligence-based methods, particularly deep learning, have shown great potential in segmenting brain tumors in contrast-enhanced MR images, which is crucial for accurate diagnosis and treatment planning in radiosurgery. To have a more accurate prediction the proposed method utilizes the MobileNet architecture. The Figure .1 below shows the general architecture of the MobileNet.

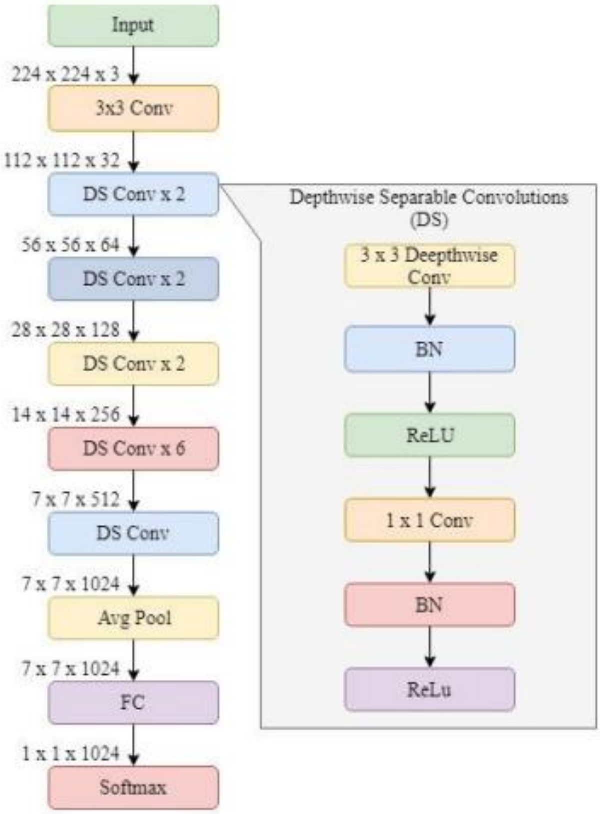



**Figure 1.** MobileNet Architecture [12]

## 3. Proposed System

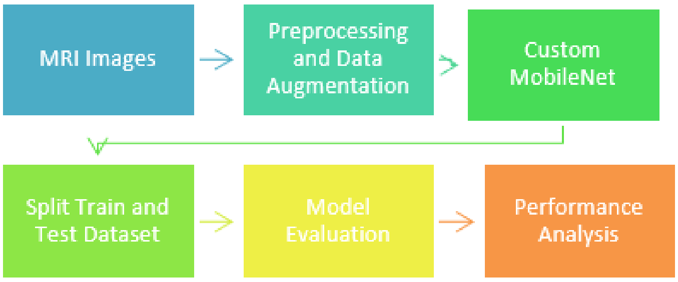



**Figure 2.** Proposed Flow Chart

The more complicated structure of the human brain motivates the design and implementation of neural networks, which act as computational simulations of the brain's capabilities. Neural networks have several applications in a variety of fields, including vector quantization, data approximation, clustering, pattern recognition, optimization functions, and classification algorithms. There are three types of neural networks: feedback, feedforward, and recurrent. The multilayer network is an important subtype of feedforward networks because it contains hidden layers that allow for complicated feature extraction and representation. An novel strategy for brain tumor classification involves exploiting the processing efficiency of MobileNet, a lightweight convolutional neural network architecture. MobileNet, with its reduced computing complexity and streamlined design, is an appealing option for real-time inference on brain imaging data. This proposed model aims to use MobileNet to accurately and efficiently classify brain tumors, allowing for the exploration of complex patterns and subtle features in medical imaging datasets while accommodating the computational constraints common in medical applications. The Figure.2 shows the different stages of the proposed method.

### 3.1 Preprocessing and Data Augmentation

Data augmentation is the process of increasing the amount and diversity of data. We do not or typically collect minimum new data; rather, we transform and change the already present or existing data. Data augmentation is an essential process in deep learning, as in deep learning we need or require large amounts and numbers of data, and in some cases, it is not possible to collect thousands or millions of images. So, data augmentation comes to the rescue. It assists us in increasing the size of the dataset and, more importantly, introduces variability in the dataset.

### 3.2 Dataset Preparation

The MRI images of the brain, captured at various pixel rates and standardized to a size of 224 x 224 pixels, were downloaded from https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset. Subsequently, the images underwent preprocessing using a NumPy array before being fed into a Keras model. They were then flattened and provided as input to the model. In a customized model, the dataset preparation included four Conv2D layers with a kernel size of 2x2, followed by four max-pooling layers with a size of 2x2. Additionally, a drop-out layer of dropout rate of 0.2 was incorporated.

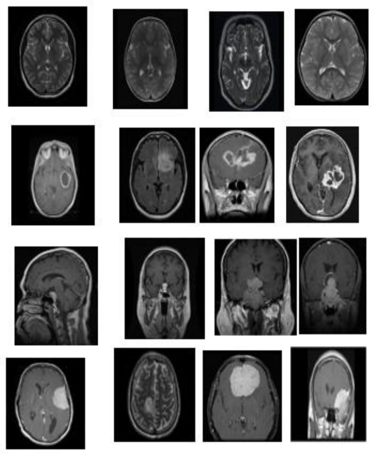


**Figure 3.** Sample Dataset

**Table 1.** Dataset Details

| S.No | Dataset Class | No Of Image |
|---|---|---|
| **1** | Normal Case | 416 |
| **2** | Beginning Case | 120 |
| **3** | Malignant Case | 561 |

### 3.3 CNN Deep NET Classifier

Deep convolutional neural networks continue to outperform various challenging visual analysis tasks. Models with parameter-rich architectures have been successfully trained and applied across a range of applications. Part of their success is attributed to the ongoing development of increasingly powerful graphics processing units (GPUs). The proposed method employs the Custom MobileNet, a CNN deep neural network architecture, for the classification of brain tumor images."

## 4. Performance Analysis

The custom CNN model resembles the suggested model but lacks Batch normalization and incorporates Dropout at the Fully connected layer. The experimental findings for the suggested model demonstrated a superior accuracy of 89.30%. The final task involves analyzing the suggested model to pinpoint the optimal tuning parameters. By evaluating the model across various train-test split ratios, it was discovered that a 70 % of dataset for training and 30% for testing resulted in enhanced accuracy. To enhance the classification accuracy even further, a Batch Normalized Convolutional Neural Network (BN-CNN) is recommended.

## 5. Performance Metrics

During the execution of the proposed framework, the effectiveness of the model's performance is assessed. This involves evaluating the rate of corrected predictions made by the model, specifically the proportion of true positive predictions to the total positive predictions generated by the model. Understanding and analyzing these metrics are essential for gauging the model's accuracy and reliability. The total count of true positive cases represents a crucial measure of precision and recall, providing a balance between the two metrics. We calculate various parameters, including accuracy, recall, and F1 score. Here, 'TP' denotes true positive, 'FP' indicates false positive, 'TN' signifies true negative, and 'FN' represents false negative

## 6. Result

The simulation code was developed using the Python language and executed in a Python environment. It involves the manipulation of multiple 2D planes using a kernel.

Training accuracy, validation accuracy, and validation loss are computed to assess efficiency. The attached images include the model import, training process, and data output

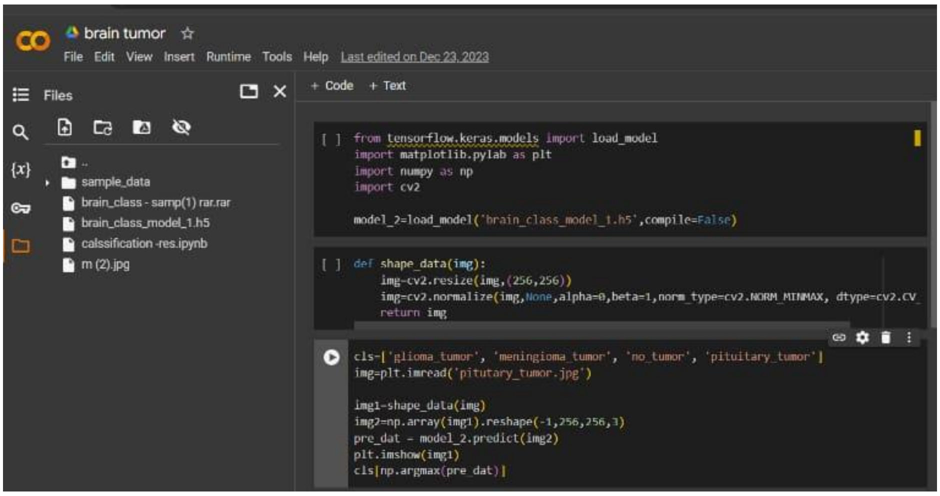
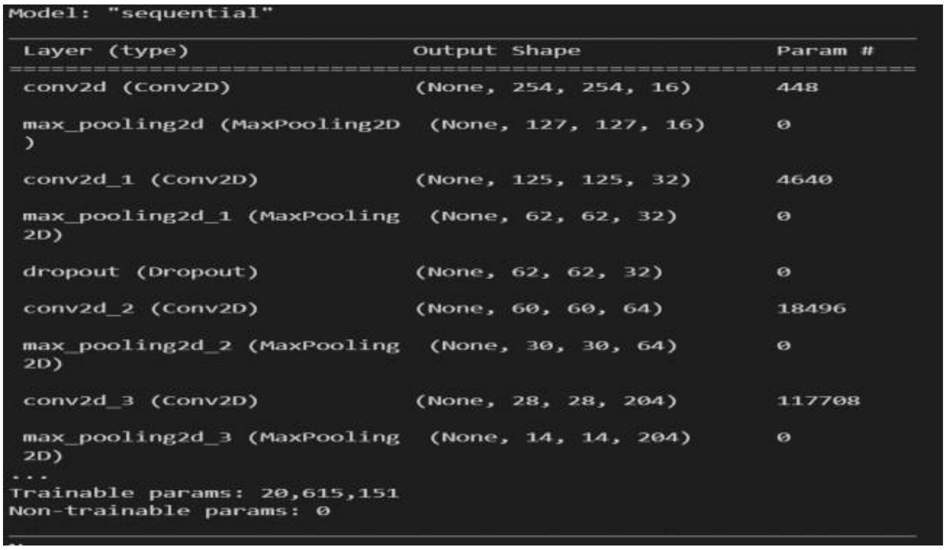



**Figure 4.** Simulation Code of Proposed



Model: "sequential"

| Layer (type) | Output Shape | Param # |
|---|---|---|
| conv2d (Conv2D) | (None, 254, 254, 16) | 448 |
| max_pooling2d (MaxPooling2D) | (None, 127, 127, 16) | 0 |
| conv2d_1 (Conv2D) | (None, 125, 125, 32) | 4640 |
| max_pooling2d_1 (MaxPooling2D) | (None, 62, 62, 32) | 0 |
| dropout (Dropout) | (None, 62, 62, 32) | 0 |
| conv2d_2 (Conv2D) | (None, 60, 60, 64) | 18496 |
| max_pooling2d_2 (MaxPooling2D) | (None, 30, 30, 64) | 0 |
| conv2d_3 (Conv2D) | (None, 28, 28, 204) | 117708 |
| max_pooling2d_3 (MaxPooling2D) | (None, 14, 14, 204) | 0 |

...
Trainable params: 20,615,151
Non-trainable params: 0

**Figure 5.** Model Description of Custom MobileNet Proposed

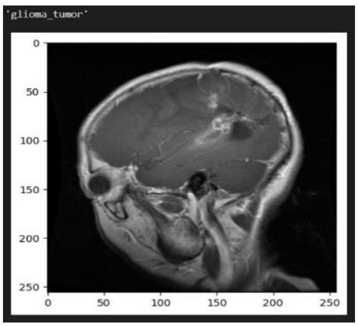



**Figure 6.** Sample Image of Tumor

## 6.1 Model Accuracy

The evaluation of the proposed frame work was carried out in the Google Colab, the graphical representation of the accuracy and the loss curves were plotted using Matplotlib. The training accuracy, depicted in the graphical plot of Figure 7, increases with the number of epochs, indicating that the model improves its ability to predict the classes of brain tumor training datasets. This rise in training accuracy signifies the model's successful capture of patterns and relationships in the training data, suggesting potential effectiveness on unseen datasets.The concurrent increase in testing accuracy, along with training accuracy, underscores the model's efficiency in learning and its potential to perform well on new, unseen datasets while avoiding overfitting

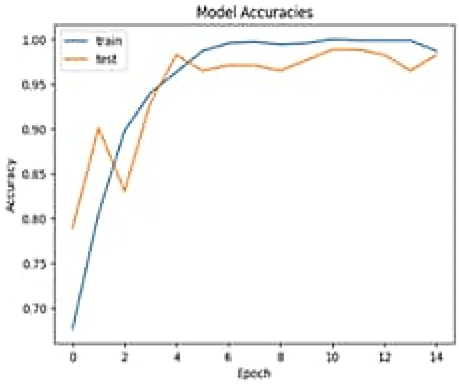



**Figure 7.** Training and Testing Accuracy

## 6.2 Model Loss

The decreasing training and testing loss depicted in Figure 8 show that the model is improving its accuracy on the training dataset. This decrease indicates that the model is learning from the training data, adjusting its parameters (weights and biases), and enhancing its performance. The decreasing testing loss suggests that the model is not overfitting to the training data but is improving its ability to make accurate predictions on unseen data. These results illustrate the model's effective learning, error minimization, and its potential to perform well on new, unseen datasets.

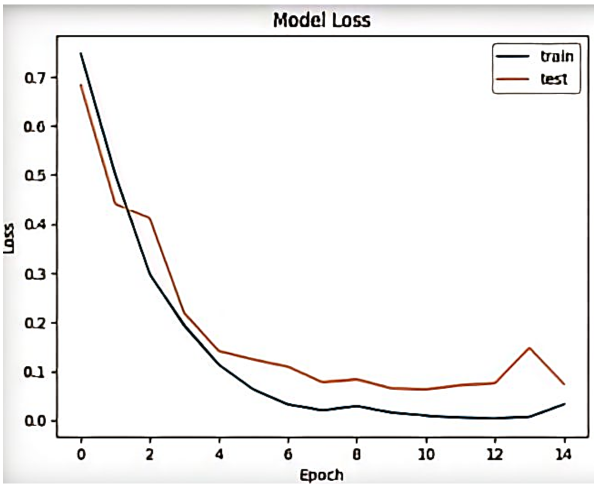



**Figure 8.** Training and Testing Loss

## 7. Conclusion

The custom MobileNet model developed showed promising results with 85% accuracy, demonstrating comparable performance to the pre-trained MobileNet model. The achieved performance underscores the model's capability to learn patterns and relationships from the training dataset, suggesting its potential effectiveness on unseen datasets. In the future, a more diverse custom dataset and additional deep learning models, including CNN variants, will be employed for the classification of brain tumor images, and the results will be compared with state-of-the-art approaches.

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