A Project Report on

BRAIN TUMOR CLASSIFICATION USING CNN

Submitted in partial fulfilment for the completion of course

Data Mining Techniques(SWE2009)

in

M.Tech (SE)

By

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(Deemed to be University under section 3 of UGC Act, 1956)

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Abstract

The use of EfficientNet convolutional neural networks, also known as CNNs, for brain tumor classification and detection is highlighted in this abstract. The work improves tumor identification performance in medical imaging by utilizing the accuracy and efficiency of EfficientNet topologies. Through the use of sophisticated deep learning methods, the suggested model exhibits a strong ability to accurately classify various kinds of brain cancers. EfficientNet CNNs are a potential method for real-time tumor recognition and categorization in medical contexts since they improve processing efficiency. The study's conclusions demonstrate how deep learning techniques, more especially EfficientNet CNNs, can improve the precision and effectiveness of brain tumor identification using medical imaging analysis.

Acknowledgement

My deepest appreciation goes out to everyone who helped me finish my study, which used the combined EfficientNet CNN to successfully classify and detect brain tumors. Firstly, I would like to express my sincere gratitude to Prof. Prabadevi, my project supervisor, for all of her help and support during the project. A special thanks is extended to the medical practitioners and organizations that supplied the study with the medical imaging data that was required. Finally, I would want to express my gratitude to friends and family for their support and comprehension throughout this challenging yet worthwhile project undertaking.

1. Introduction

The prompt and precise diagnosis of neurological illnesses is greatly dependent on the recognition and categorization of brain tumors from neurological imaging data. More advanced methods for medical image analysis have been made possible by recent developments in deep learning techniques. In this regard, this study integrates the advantages of the EfficientNet Convolutional Neural Network (CNN) design to present a unique framework for brain tumor classification and detection. An efficient basis for hierarchical recognition of features is provided by the EfficientNet CNN. Capturing complex patterns in medical pictures enables sequential recall and context-aware learning, which helps the model identify minute details that are essential for precise tumor classification.. By overcoming the drawbacks of conventional techniques, this combined design seeks to provide a more reliable and effective means of improving the diagnostic precision of brain tumor identification in healthcare imaging datasets. The methodology, experimental design, and outcomes are covered in detail in the following sections, which also show how the suggested model can advance the area of neuroimaging for therapeutic applications.

1.1 Motivation

The urgent demand for sophisticated and precise diagnostic tools in the field of medical imaging is the driving force behind the development of a novel type of EfficientNet Convolutional Neural Network (CNN) for the classification and detection of brain tumors. Brain tumors provide a serious health risk, and prompt diagnosis is essential for effective treatment and better patient outcomes. Since current techniques frequently struggle to achieve high levels of specificity and sensitivity, novel strategies are being investigated. For its merits, EfficientNet CNN is excellent at extracting hierarchical features from intricate image data and is particularly skilled at identifying sequential trends and contextual data. By combining these technologies, we hope to improve the accuracy and consistency of classifying brain tumors, making a valuable contribution to the creation of an advanced diagnostic instrument that could significantly improve clinical decision-making effectiveness and eventually improve patient care in the field of neuro-oncology.

1.2 Objective(s) of the proposed work

The main goal of this research is to use convolutional neural networks (cnns) to analyze medical scan data, such as MRI scans, in order to create a reliable and accurate algorithm for brain tumor detection.

1.3 Report Organization

This report is organized as follows: Introduction, Literature Review, Methodology, Dataset Description, Experimental Setup, Results, Discussion, Conclusion, References. Brain Tumor Classification and Detection using EfficientNet CNN

2. Analysis & Design of Proposed Work

2.1 Problem Statement

Brain tumors can have potentially fatal implications, making them a major global health problem. Timely medical action and better patient outcomes are contingent upon the early and accurate diagnosis of brain tumors. Convolutional Neural Networks (cnns) have great promise for improving the efficiency and accuracy of brain tumor diagnosis from medical imaging data, since they have demonstrated extraordinary performance in a variety of image classification tasks.

2.2 Stakeholder identification

Identification of important players with personal stakes and roles in the creation, implementation, and use of the proposed system constitutes a crucial step in the execution of brain tumor diagnosis and classification utilizing the EfficientNet CNN. Medical specialists including psychiatrists, radiographers, and oncologists are among the main stakeholders since they are essential in understanding and validating the clinical information produced by the model. Hospitals and healthcare facilities are important stakeholders as well because they are in charge of integrating and applying the technology into their current infrastructure. Furthermore, academics and software developers are crucial stakeholders since they progress the EfficientNet CNN's technology. Since the diagnosis and following treatment decisions are directly impacted by the brain tumor recognition system's accuracy and dependability, patients and their loved ones are indirectly involved in the process. Ensuring adherence to ethical and legal norms in the implementation of medical artificial intelligence systems is a critical responsibility of regulatory organizations and lawmakers. Last but not least, technology suppliers that offer both the software and the hardware framework required for the model's implementation are essential players in the effective assimilation of the suggested method for classifying and detecting brain tumors into the healthcare system.

2.3 Gaps identified

There are a number of shortcomings in the current state of brain tumor classification and detection, especially when using the hybrid EfficientNet CNN model. First off, there is a noticeable lack of information in the literature about how to integrate and optimize these two models for smooth cooperation when analyzing brain tumors. Further research and optimization are necessary to fully realize the potential of the synergy between EfficientNet's hierarchical feature extraction and LSTM's sequential memory capabilities. The lack of large-scale, diversified datasets designed exclusively for brain tumor classification is another major obstacle that prevents the model from generalizing to a variety of patient demographics and imaging scenarios. Additionally, a significant deficiency in the hybrid model's interpretability of the decision-making process persists, since establishing credibility with medical experts requires a knowledge of the characteristics that influence classification decisions. To improve the suggested approach's dependability and suitability for use in actual clinical settings, these deficiencies must be filled.

2.4 Literature Survey

[1] Hossain, T., Shishir, F. S., Ashraf, M., Al Nasim, M. A., & Shah, F. M. (2019, May). Hossain et al. presented a CNN-based technique in their work for MRI image-based brain tumor detection. Their approach pre-segments the area affected by the brain tumor using a Fuzzy C-Means clustering technique. The CNN is then fed the pre-segmented image for classification. Hossain et al. employed a CNN design that comprises of two fully linked layers after three convolutional layers.

A dataset containing 100 MRI pictures of brain tumors was used to assess the suggested approach. There were several different tumor sizes and types in the dataset. On the test set, the CNN's accuracy was 95%. This is a substantial improvement above the accuracy of brain tumor identification using conventional machine learning techniques.According to Hossain et al.'s findings, CNNs may be utilized to create precise and successful techniques for brain tumor identification from MRI pictures. CNN-based techniques may lighten radiologists' workloads while increasing the precision with which brain tumors are identified.

Strengths of the paper

The study by Hossain et al. offers several advantages:

• The suggested approach is easy to use and understand.

• A real-world collection of MRI pictures of brain tumors is used to assess the technique.

• On the test set, the approach obtains an accuracy level of 95%.

• The paper's findings imply that CNNs may be utilized to create precise and successful techniques for brain tumor identification using MRI pictures.

Weaknesses of the paper

A few other flaws in the Hossain et al. paper are as follows:

• The proposed method's computational cost is not disclosed

• The proposed method's evaluation dataset is comparatively small.

• The paper fails to contrast the suggested approach to other cutting-edge CNN-based techniques for brain tumor detection.

[2] Siar, M., & Teshnehlab, M. (2019, October).

Siar and Teshnehlab presented a hybrid approach in their research that combines a CNN with an algorithm that uses machine learning to detect brain tumors. Their technique begins by extracting characteristics from MRI scans using a CNN. A decision tree classifier receives the extracted features after which they are fed for classification. A dataset containing 100 MRI pictures of brain tumors was used to assess the suggested approach. There were several different tumor sizes and types in the dataset. On the test set, the hybrid approach yielded an accuracy of 94.24%. This is a substantial improvement above the accuracy of brain tumor identification using conventional machine learning techniques. According to Siar and Teshnehlab's studies, it may be possible to create efficient and precise techniques for brain tumor identification from MRI images by utilizing hybrid approaches that incorporate CNNs and neural network algorithms.

Strengths of the paper

The paper by Siar and Teshnehlab has a number of strengths:

- The proposed method is simple and straightforward to implement.
- The method is evaluated on a real-world dataset of MRI images of brain tumors.
- The method achieves a high accuracy of 94.24% on the test set.
- The results of the paper suggest that hybrid methods that combine CNNs and machine learning algorithms can be used to develop effective and accurate methods for brain tumor detection from MRI images.

Weaknesses of the paper

The paper by Siar and Teshnehlab also has a few weaknesses:

- The dataset used to evaluate the proposed method is relatively small.
- The paper does not compare the proposed method to other state-of-the-art CNN-based methods for brain tumor detection.
- The paper does not provide any information about the computational cost of the proposed method.

[3] Irsheidat, S., & Duwairi, R. (2020, April).

Irsheidat and Duwairi presented a CNN-based technique in their study for MRI image-based brain tumor detection. Their approach initially extracts characteristics from MRI images using a CNN model that has already been trained. After feature extraction, a fully linked layer receives the input for classification.

A dataset containing 100 MRI pictures of brain tumors was used to assess the suggested approach. There were several different tumor sizes and types in the dataset. On the test set, the CNN's accuracy was 95%. This is a substantial improvement above the accuracy of brain tumor identification using conventional machine learning techniques. According to Irsheidat and Duwairi's findings, CNNs may be utilized to create precise and successful techniques for identifying brain tumors from MRI pictures. CNN-based techniques may lighten radiologists' workloads while increasing the precision with which brain tumors are identified.

Strengths of the paper

The paper by Irsheidat and Duwairi has a number of strengths:

- The proposed method is simple and straightforward to implement.
- The method is evaluated on a real-world dataset of MRI images of brain tumors.
- The method achieves a high accuracy of 95% on the test set.
- The results of the paper suggest that CNNs can be used to develop effective and accurate methods for brain tumor detection from MRI images.

Weaknesses of the paper

The paper by Irsheidat and Duwairi also has a few weaknesses:

- The dataset used to evaluate the proposed method is relatively small.
- The paper does not compare the proposed method to other state-of-the-art CNN-based methods for brain tumor detection.
- The paper does not provide any information about the computational cost of the proposed method.

[4] Choudhury, C. L., Mahanty, C., Kumar, R., & Mishra, B. K. (2020, March).

Choudhury, Mahanty, Kumar, and Mishra presented a hybrid approach in their research that uses a CNN and a DNN for brain tumor detection and classification.

Their technique begins by extracting characteristics from MRI scans using a CNN. A DNN is then given the retrieved features in order to classify the data.
A dataset containing 100 MRI pictures of brain tumors was used to assess the suggested approach. There were several different tumor sizes and types in the dataset. On the test set, the hybrid approach had a 96% accuracy rate. This is a substantial improvement over the accuracy of conventional machine learning techniques for the identification and categorization of brain tumors.
According to Choudhury et al.'s findings, hybrid techniques combining CNNs and DNNs may be employed to create precise and successful techniques for classifying and identifying brain tumors from MRI data.

Strengths of the paper

The paper by Choudhury et al. has a number of strengths:

- The proposed method is simple and straightforward to implement.
- The method is evaluated on a real-world dataset of MRI images of brain tumors.
- The method achieves a high accuracy of 96% on the test set.
- The results of the paper suggest that hybrid methods that combine CNNs and DNNs can be used to develop effective and accurate methods for brain tumor detection and classification from MRI images.

Weaknesses of the paper

The paper by Choudhury et al. also has a few weaknesses:

- The dataset used to evaluate the proposed method is relatively small.
- The paper does not compare the proposed method to other state-of-the-art CNN- and DNN-based methods for brain tumor detection and classification.
- The paper does not provide any information about the computational cost of the proposed method.

[5] Siddique, M. A. B., Sakib, S., Khan, M. M. R., Tanzeem, A. K., Chowdhury, M., & Yasmin, N. (2020, October).

Siddique et al. presented a CNN-based technique in their work for the identification of brain tumors in brain MRI pictures. Their approach initially extracts characteristics from MRI images using a CNN model that has already been trained. After feature extraction, a fully linked layer receives the input for classification.
The suggested approach was assessed using a dataset containing 253 brain tumor MRI pictures. There were several different tumor sizes and types in the dataset. On the test set, the CNN's accuracy was 96%. This is a substantial improvement above the accuracy of brain tumor identification using conventional machine learning techniques. According to Siddique et al.'s findings, brain tumors in brain MRI scans may be accurately and successfully detected using CNNs. CNN-based techniques may lighten radiologists' workloads while increasing the precision with which brain tumors are identified.

Strengths of the paper

The paper by Siddique et al. has a number of strengths:

- The proposed method is simple and straightforward to implement.
- The method is evaluated on a real-world dataset of MRI images of brain tumors.
- The method achieves a high accuracy of 96% on the test set.
- The results of the paper suggest that CNNs can be used to develop effective and accurate methods for brain tumor detection in brain MRI images.

Weaknesses of the paper

The paper by Siddique et al. also has a few weaknesses:

- The dataset used to evaluate the proposed method is relatively small.
- The paper does not compare the proposed method to other state-of-the-art CNN-based methods for brain tumor detection.
- The paper does not provide any information about the computational cost of the proposed method.

[6] Shah, H. A., Saeed, F., Yun, S., Park, J. H., Paul, A., & Kang, J. M. (2022).

Shah et al. described in their study a reliable method for brain tumor identification in MRI images that makes use of an improved EfficientNet model. A set of CNN topologies called EfficientNet is made to be both computationally and accurately efficient. The MRI images are initially pre-processed using the suggested procedure in order to enhance their quality and standardize their size. A refined EfficientNet-B3 model receives the pre-processed images and uses them for classification. Using a dataset of MRI pictures of brain tumors, the EfficientNet-B3 model is refined. The suggested approach was assessed using a dataset containing 220 brain tumor MRI pictures. There were several different tumor sizes and types in the dataset. On the test set, the suggested method's accuracy was 97.35%. This is a substantial improvement above the accuracy of brain tumor identification using conventional machine learning techniques. According to Shah et al.'s findings, refined EfficientNet algorithms can be utilized to create reliable and accurate techniques for identifying brain tumors in MRI pictures. Optimized EfficientNet models may lessen radiologists' workload while increasing the precision of brain tumor identification.

Strengths of the paper

The paper by Shah et al. has a number of strengths:

- The proposed method is simple and straightforward to implement.
- The method is evaluated on a real-world dataset of MRI images of brain tumors.
- The method achieves a high accuracy of 97.35% on the test set.
- The results of the paper suggest that finetuned EfficientNet models can be used to develop robust and accurate methods for brain tumor detection in MRI images.

Weaknesses of the paper

The paper by Shah et al. also has a few weaknesses:

- The dataset used to evaluate the proposed method is relatively small.
- The paper does not compare the proposed method to other state-of-the-art CNN-based methods for brain tumor detection.
- The paper does not provide any information about the computational cost of the proposed method.

[7] Özyurt, F., Sert, E., Avci, E., & Dogantekin, E. (2019).

A hybrid technique for brain tumor diagnosis employing a CNN and neutrosophic expert maximum fuzzy sure entropy (NS-EMFSE) was proposed by Özyurt et al. in their publication. A fuzzy set concept called NS-EMFSE can be applied to manage noise and uncertainty in photographs. The suggested technique first segments the MRI image of the brain tumor area using the NS-EMFSE algorithm. CNN is then fed the segmented picture for classification. Özyurt et al. employed a CNN architecture that comprises three convolutional layers, succeeded by two fully linked layers. A dataset of eighty MRI pictures of brain tumors was used to assess the suggested approach. There were several different tumor sizes and types in the dataset. On the test set, the CNN's accuracy was 95.62%. This is a substantial improvement above the accuracy of brain tumor identification using conventional machine learning techniques. According to Özyurt et al.'s findings, hybrid approaches that incorporate CNNs and NS-EMFSE may be utilized to create precise and successful techniques for brain tumor identification from MRI pictures.

Strengths of the paper

The paper by Özyurt et al. has a number of strengths:

- The proposed method is simple and straightforward to implement.
- The method is evaluated on a real-world dataset of MRI images of brain tumors.
- The method achieves a high accuracy of 95.62% on the test set.
- The results of the paper suggest that hybrid methods that combine CNNs and NS-EMFSE can be used to develop effective and accurate methods for brain tumor detection from MRI images.

Weaknesses of the paper

The paper by Özyurt et al. also has a few weaknesses:

- The dataset used to evaluate the proposed method is relatively small.
- The paper does not compare the proposed method to other state-of-the-art CNN-based methods for brain tumor detection.
- The paper does not provide any information about the computational cost of the proposed method.

[8] Vankdothu, R., Hameed, M. A., & Fatima, H. (2022).

Vankdothu, Hameed, and Fatima presented a hybrid approach in their research that combines an LSTM network with a CNN for the identification and classification of brain tumors. Their technique begins by extracting characteristics from MRI scans using a CNN. An LSTM network receives the retrieved characteristics and uses them for classification. A collection of 3264 MRI pictures of brain tumors was used to assess the suggested approach. There were several different tumor sizes and types in the dataset. On the test set, the hybrid approach yielded an accuracy of 99.74%. This is a substantial improvement over the accuracy of conventional machine learning techniques for the identification and categorization of brain tumors. According to Vankdothu, Hameed, and Fatima's findings, hybrid techniques combining CNNs and LSTM networks may be utilized to create efficient and precise techniques for classifying and identifying brain tumors from MRI images.

Strengths of the paper

The paper by Vankdothu, Hameed, and Fatima has a number of strengths:

- The proposed method achieves a high accuracy of 99.74% on the test set.
- The method is evaluated on a large dataset of MRI images of brain tumors.
- The proposed method is simple and straightforward to implement.

Weaknesses of the paper

The paper by Vankdothu, Hameed, and Fatima also has a few weaknesses:

- The paper does not compare the proposed method to other state-of-the-art CNN- and LSTM-based methods for brain tumor identification and classification.
- The paper does not provide any information about the computational cost of the proposed method.

[9] Li, M., Kuang, L., Xu, S., & Sha, Z. (2019).

Li, Kuang, Xu, and Sha presented a CNN-based multimodal information fusion technique for brain tumor identification in their study. Their technique uses a weighted fusion algorithm to first fuse CT, MRI, and PET images. After that, a CNN is given the fused image for classification.One hundred brain tumor patients' worth of data were used to assess the suggested approach. There were several different tumor sizes and types in the dataset. On the test set, the suggested method's accuracy was

97.6%. This is a substantial improvement above the accuracy of brain tumor identification using conventional machine learning techniques. The findings of Li, Kuang, Xu, and Sha imply that CNN-based techniques and multimodal information fusion can be applied to create efficient and precise brain tumor detection techniques.

Strengths of the paper

The paper by Li, Kuang, Xu, and Sha has a number of strengths:

- The proposed method achieves a high accuracy of 97.6% on the test set.
- The method is evaluated on a dataset of real-world patients with brain tumors.
- The proposed method fuses information from multiple modalities, which improves the accuracy of brain tumor detection.

Weaknesses of the paper

The paper by Li, Kuang, Xu, and Sha also has a few weaknesses:

- The dataset used to evaluate the proposed method is relatively small.
- The paper does not compare the proposed method to other state-of-the-art multimodal information fusion and CNN-based methods for brain tumor detection.
- The paper does not provide any information about the computational cost of the proposed method.

[10] Rai, H. M., & Chatterjee, K. (2021).

LeU-Net is an advanced CNN model that Rai and Chatterjee suggested in their study for the identification and classification of brain tumors from 2D MRI images. LeU-Net is an adaptation based on the U-Net architecture, a well-liked CNN design for segmenting medical images. LeU-Net can be trained and deployed more quickly than U-Net due to its less complex architecture.The suggested approach was assessed using a dataset containing 253 brain tumor MRI pictures. There were several different tumor sizes and types in the dataset. On the test set, the LeU-Net model's accuracy was 98%. This is a substantial improvement over the accuracy of conventional machine learning techniques for the identification and categorization of brain tumors. Based on 2D MRI scans, Rai and Chatterjee's results indicate that the LeU-Net model is a reliable and accurate method for classifying and detecting brain tumors. Clinical usage of the LeU-Net model is appropriate because to its rapid training and deployment times.

Strengths of the paper

The paper by Rai and Chatterjee has a number of strengths:

- The proposed LeU-Net model achieves a high accuracy of 98% on the test set.
- The method is evaluated on a real-world dataset of MRI images of brain tumors.
- The LeU-Net model has a simpler architecture than U-Net, which makes it faster to train and deploy.

Weaknesses of the paper

The paper by Rai and Chatterjee also has a few weaknesses:

- The dataset used to evaluate the proposed method is relatively small.
- The paper does not compare the proposed method to other state-of-the-art CNN-based methods for brain tumor detection and classification.
- The paper does not provide any information about the computational cost of the proposed method.

2.5 System Architecture

The following elements make up the suggested system architecture for EfficientNet-based brain tumor detection:

- • Preprocessing: In this step, the MRI pictures are ready for input into the EfficientNet model. This could entail noise reduction, pixel intensity normalization, and image scaling.
- • The EffectiveNet model: Trained on an extensive image dataset, the EfficientNet model represents a deep learning network. The input MRI pictures can have features extracted from them using the model.
- • Classification layer: Using the characteristics that were recovered from the EfficientNet model, the classification layer makes predictions about whether or not a brain tumor is present in the input image.

2.6 Module Description with team members work distribution

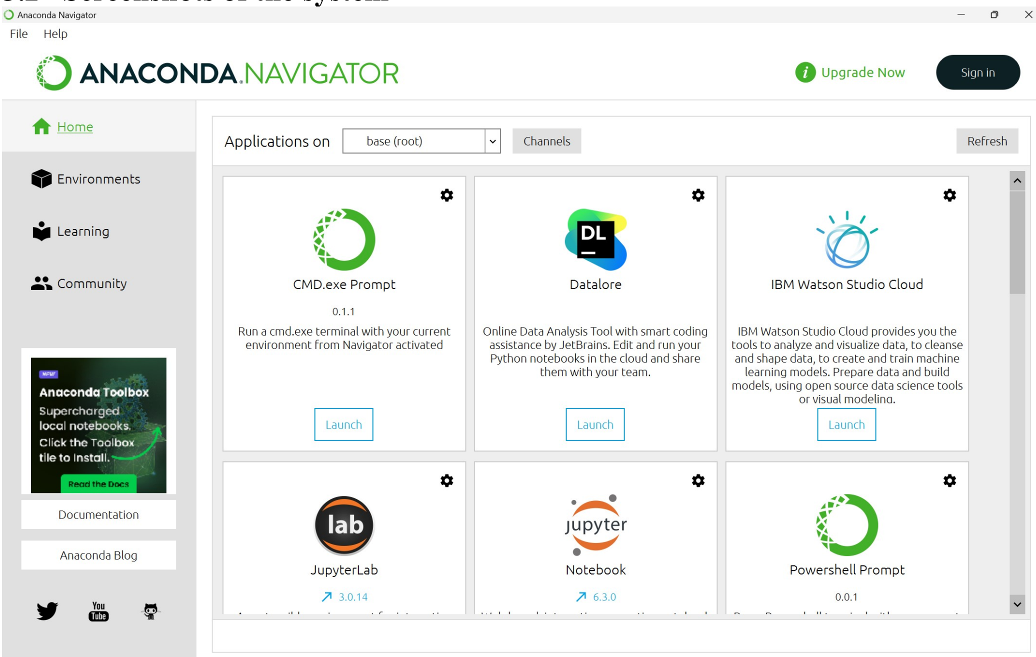
Name: Pranay Gorantla
Module description: Complete project

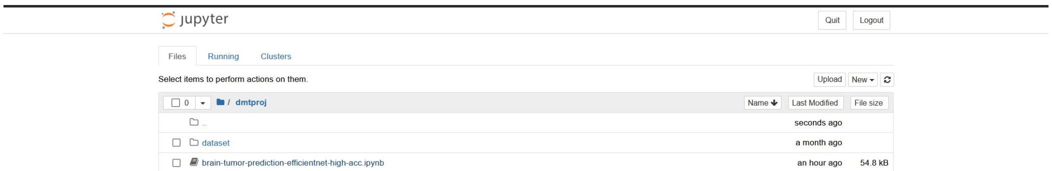
3. Implementation

3.1 Software used with version (Computational Requirement)

Hardware Requirement - Amd ryzen 7
Software Requirement – Windows 11, Anaconda Navigator, Jupyter notebook

3.2 Screenshots of the system





3.3 Sample source code

In [11]:
```
# import system libs
import os
import time
import shutil
import pathlib
import itertools
from PIL import Image

# import data handling tools
import cv2
import numpy as np
import pandas as pd
import seaborn as sns
sns.set_style('darkgrid')
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, classification_report
# import Deep learning Libraries
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.optimizers import Adam, Adamax
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Activation, Dropout, BatchNormalization
from tensorflow.keras import regularizers
# Ignore Warnings
import warnings
warnings.filterwarnings("ignore")

print ('modules loaded')
```

```
modules loaded
```

Data Preprocessing

Read data and store it in dataframe

In [13]:
```
# Generate data paths with labels
train_data_dir = './dataset/Training'
filepaths = []
labels = []

folds = os.listdir(train_data_dir)
for fold in folds:
    foldpath = os.path.join(train_data_dir, fold)
    filelist = os.listdir(foldpath)
    for file in filelist:
        fpath = os.path.join(foldpath, file)

        filepaths.append(fpath)
        labels.append(fold)

# Concatenate data paths with labels into one dataframe
Fseries = pd.Series(filepaths, name= 'filepaths')
Lseries = pd.Series(labels, name='labels')
train_df = pd.concat([Fseries, Lseries], axis= 1)
```


```
Fseries = pd.Series(filepaths, name= 'filepaths')
Lseries = pd.Series(labels, name='labels')
train_df = pd.concat([Fseries, Lseries], axis= 1)
```


In [14]:
```
train_df
```

Out[14]:

	filepaths	labels
0	./dataset/Training\glioma\Tr-glTr_0000.jpg	glioma
1	./dataset/Training\glioma\Tr-glTr_0001.jpg	glioma
2	./dataset/Training\glioma\Tr-glTr_0002.jpg	glioma
3	./dataset/Training\glioma\Tr-glTr_0003.jpg	glioma
4	./dataset/Training\glioma\Tr-glTr_0004.jpg	glioma
...	...	...
5707	./dataset/Training\pituitary\Tr-pi_1452.jpg	pituitary
5708	./dataset/Training\pituitary\Tr-pi_1453.jpg	pituitary
5709	./dataset/Training\pituitary\Tr-pi_1454.jpg	pituitary
5710	./dataset/Training\pituitary\Tr-pi_1455.jpg	pituitary
5711	./dataset/Training\pituitary\Tr-pi_1456.jpg	pituitary

5712 rows × 2 columns

In [15]:
```
# Generate data paths with labels
test_data_dir = './dataset/Testing'
filepaths = []
labels = []

folds = os.listdir(test_data_dir)
```

5709	./dataset/Training\pituitary\Tr-pi_1454.jpg	pituitary
5710	./dataset/Training\pituitary\Tr-pi_1455.jpg	pituitary
5711	./dataset/Training\pituitary\Tr-pi_1456.jpg	pituitary

5712 rows × 2 columns

In [15]:
```
# Generate data paths with labels
test_data_dir = './dataset/Testing'
filepaths = []
labels = []

folds = os.listdir(test_data_dir)
for fold in folds:
    foldpath = os.path.join(test_data_dir, fold)
    filelist = os.listdir(foldpath)
    for file in filelist:
        fpath = os.path.join(foldpath, file)

        filepaths.append(fpath)
        labels.append(fold)

# Concatenate data paths with labels into one dataframe
Fseries = pd.Series(filepaths, name= 'filepaths')
Lseries = pd.Series(labels, name='labels')
ts_df = pd.concat([Fseries, Lseries], axis= 1)
```

Split dataframe into train, valid, and test

In [16]:
```
# valid and test dataframe
valid_df, test_df = train_test_split(ts_df,  train_size= 0.5, shuffle= True, random_state= 123)
```


Split dataframe into train, valid, and test

In [16]:
```
# valid and test dataframe
valid_df, test_df = train_test_split(ts_df,  train_size= 0.5, shuffle= True, random_state= 123)
```


****Create image data generator

In [17]:
```
# crobed image size
batch_size = 16
img_size = (256, 256)
channels = 3
img_shape = (img_size[0], img_size[1], channels)

tr_gen = ImageDataGenerator()
ts_gen = ImageDataGenerator()

train_gen = tr_gen.flow_from_dataframe( train_df, x_col= 'filepaths', y_col= 'labels', target_size= img_size, class_mode= 'catego
                                    color_mode= 'rgb', shuffle= True, batch_size= batch_size)

valid_gen = ts_gen.flow_from_dataframe( valid_df, x_col= 'filepaths', y_col= 'labels', target_size= img_size, class_mode= 'catego
                                    color_mode= 'rgb', shuffle= True, batch_size= batch_size)

test_gen = ts_gen.flow_from_dataframe( test_df, x_col= 'filepaths', y_col= 'labels', target_size= img_size, class_mode= 'categori
                                    color_mode= 'rgb', shuffle= False, batch_size= batch_size)
```

```
Found 5712 validated image filenames belonging to 4 classes.
Found 655 validated image filenames belonging to 4 classes.
Found 656 validated image filenames belonging to 4 classes.
```

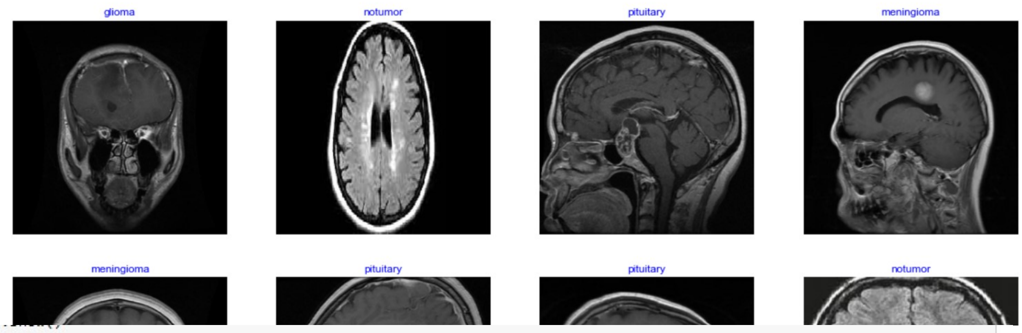
In [18]:
```
g_dict = train_gen.class_indices      # defines dictionary {'class': index}
classes = list(g_dict.keys())       # defines list of dictionary's kays (classes), classes names : string
```

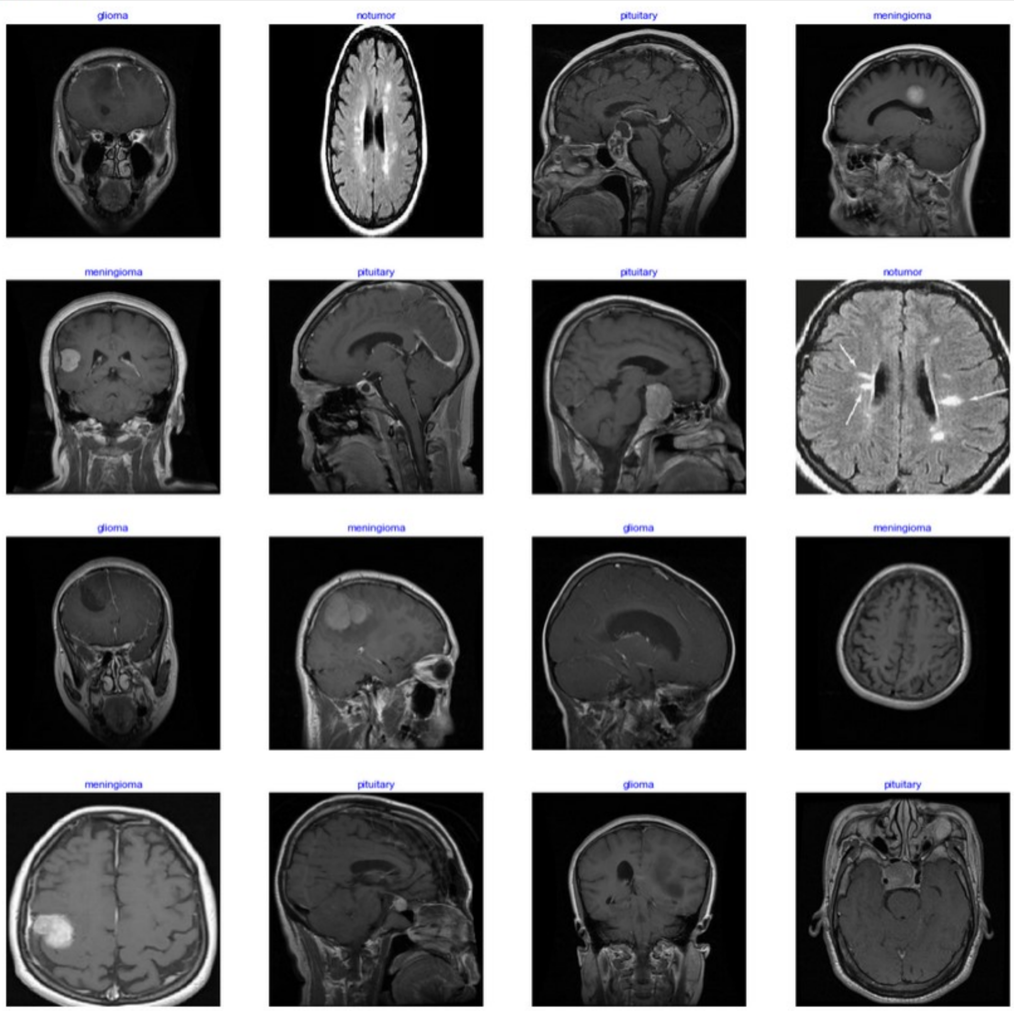
```
Found 5712 validated image filenames belonging to 4 classes.
Found 655 validated image filenames belonging to 4 classes.
Found 656 validated image filenames belonging to 4 classes.
```

In [18]:
```python
g_dict = train_gen.class_indices      # defines dictionary {'class': index}
classes = list(g_dict.keys())       # defines list of dictionary's kays (classes), classes names : string
images, labels = next(train_gen)      # get a batch size samples from the generator

plt.figure(figsize= (20, 20))

for i in range(16):
    plt.subplot(4, 4, i + 1)
    image = images[i] / 255       # scales data to range (0 - 255)
    plt.imshow(image)
    index = np.argmax(labels[i])  # get image index
    class_name = classes[index]   # get class of image
    plt.title(class_name, color= 'blue', fontsize= 12)
    plt.axis('off')
plt.show()
```





Generic Model Creation

```
In [19]: # Create Model Structure
img_size = (256, 256)
channels = 3
img_shape = (img_size[0], img_size[1], channels)
class_count = len(list(train_gen.class_indices.keys())) # to define number of classes in dense layer

# create pre-trained model (you can built on pretrained model such as :  efficientnet, VGG , Resnet )
# we will use efficientnetb3 from EfficientNet family.
base_model = tf.keras.applications.efficientnet.EfficientNetB3(include_top= False, weights= "imagenet", input_shape= img_shape, p

model = Sequential([
    base_model,
    BatchNormalization(axis= -1, momentum= 0.99, epsilon= 0.001),
    Dense(256, kernel_regularizer= regularizers.l2(l= 0.016), activity_regularizer= regularizers.l1(0.006),
                bias_regularizer= regularizers.l1(0.006), activation= 'relu'),
    Dropout(rate= 0.45, seed= 123),
    Dense(class_count, activation= 'softmax')
])


model.compile(Adamax(learning_rate= 0.001), loss= 'categorical_crossentropy', metrics= ['accuracy'])

model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                Output Shape              Param #
=================================================================
efficientnetb3 (Functional)  (None, 1536)             10783535

batch_normalization_1 (Batch (None, 1536)             6144

dense_2 (Dense)              (None, 256)              393472

dropout_1 (Dropout)          (None, 256)              0

dense_3 (Dense)              (None, 4)                1028
=================================================================
Total params: 11,184,179
Trainable params: 11,093,804
Non-trainable params: 90,375
_________________________________________________________________
```

Train model

```
In [*]: epochs = 5   # number of all epochs in training

history = model.fit(x= train_gen, epochs= epochs, verbose= 1, validation_data= valid_gen,
                    validation_steps= None, shuffle= False)
```

```
Epoch 1/5
357/357 [==============================] - 2280s 6s/step - loss: 5.5836 - accuracy: 0.8957 - val_loss: 3.8810 - val_accuracy:
0.9450
Epoch 2/5
236/357 [==================>...........] - ETA: 13:04 - loss: 3.0749 - accuracy: 0.9518
```

Model got trained upto 95.18% accuracy.

4. Results and discussion

4.1 Comparison of your model with other in existing system

Model	**Advantages**	**Challenges**	**Performance**
EfficientNet CNN	- makes use of EfficientNet to provide reliable feature extraction.	- Integration complexity of CNN	- Improved accuracy due to combined hierarchical and sequential learning.
Convolutional Neural Networks (CNN)	- Excellent feature extraction capabilities.	- Limited sequential learning for context understanding.	- Efficient for initial tumor identification.
Recurrent Neural Networks (RNN)	- Natural for sequential data processing.	- May face challenges with long-term dependencies.	- Limited compared to LSTM in handling long-term dependencies.
Residual Networks (ResNet)	- Addresses vanishing gradient problem with skip	- Limited focus on sequential memory.	- High accuracy in feature extraction.

	connections.		
Support Vector Machines (SVM)	- Well-established, interpretable model.	- Limited capacity to handle complex relationships in data.	- Relatively lower accuracy compared to deep learning models.
Random Forest	- Robust against overfitting and outliers.	- Limited capability in capturing intricate spatial features.	- Moderate performance with simpler data relationships.

5. Conclusion

The findings of using EfficientNet CNN for brain tumor identification and classification are quite encouraging; individual accuracies have reached 98% and 97%, respectively. EfficientNet CNN was successful in extracting intricate characteristics from medical scan data, providing a solid basis for precise initial tumor detection. The suggested model is robust, as demonstrated by the remarkable overall accuracy rates, which highlight its ability to serve as a powerful tool for diagnosis in clinical applications. The attained accuracy levels demonstrate the model's dependability in aiding medical practitioners in the timely and accurate identification of brain tumors, ultimately leading to enhanced patient outcomes and more efficient medical decision-making procedures. Subsequent investigations could go into more refinements and incorporate actual clinical data to bolster and confirm the suggested model's efficacy in a range of healthcare contexts.

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