A PROJECT REPORT

on

"CELEBRAL WATCH: Tumor Monitoring"

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In Partial Fulfilment of the Requirement for the Award of

BACHELOR'S DEGREE IN
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TABLE OF CONTENTS

ABSTRACT

Nowadays, tumors are the second leading cause of cancer. Because of cancer, a large number of patients are in danger. The medical field requires a fast, automated, efficient, and dependable technique to detect tumors such as brain tumors. Detection is extremely important in treatment. If proper tumor detection is possible, doctors can keep a patient safe. This application makes use of various image processing techniques. Doctors use this application to provide proper treatment and save the lives of many tumor patients. A tumor is simply an accumulation of excess cells that grow uncontrollably. Brain tumor cells grow in such a way that they eventually absorb all of the nutrients intended for healthy cells and tissues, resulting in brain failure. Currently, doctors locate the position and the location of the brain tumor by manually reviewing the patient's MRI images. This leads to inaccurate tumor detection and is time-consuming. A tumor is a mass of tissue that has grown out of control. We can detect brain tumors using Deep Learning architectures such as CNN (Convolution Neural Network), also known as NN (Neural Network), and VGG 19 (visual geometry group) Transfer Learning. The model's performance is to predict whether or not a tumor is present in an image. If the tumor is present, return yes; otherwise, return no.

Keywords: Brain tumors, MRI, Convolution Neural Network, VGG19,

I. INTRODUCTION

A. BRAIN TUMOR DETECTION SYSTEM:

The human body is made up of many organs, with the brain being the most critical and vital. Brain tumors are one of the most common causes of brain dysfunction. A tumor is simply an accumulation of excess cells that grow uncontrollably. Brain tumor cells grow in such a way that they eventually absorb all of the nutrients intended for healthy cells and tissues, resulting in brain failure. Doctors currently use manual examination of the patient's MR images to determine the position and area of the brain tumor. This leads to inaccurate tumor detection and is time-consuming.

Brain cancer is a critical disease that kills many people. A system for detecting and classifying brain tumors is available, allowing for early diagnosis. Cancer classification is the most difficult task in clinical diagnosis. This project focuses on a system that uses computer-based procedures to detect tumor blocks and classify tumor types from MRI images of various patients using the Convolution Neural Network Algorithm.

Different image processing techniques, such as image segmentation, image enhancement, and feature extraction, are used to detect brain tumors in MRI images of cancer patients. Detecting brain tumors using image processing techniques consists of four stages: image pre-processing, image segmentation, feature extraction, and classification.

Image processing and neural network techniques are used to improve the accuracy of detecting and classifying brain tumors in MRI images.

B. OVERVIEW OF BRAIN AND BRAIN TUMOR:

The brain is the main component of the human neurological system. It is found in the human head, and the skull covers it. The purpose of the human brain is to regulate every bodily part. It is one form of organ that enables people to adapt to and withstand any kind of environmental circumstance. Humans are able to act and communicate their thoughts and feelings thanks to the human brain. This section explains how the brain is structured to comprehend the most fundamental concepts.

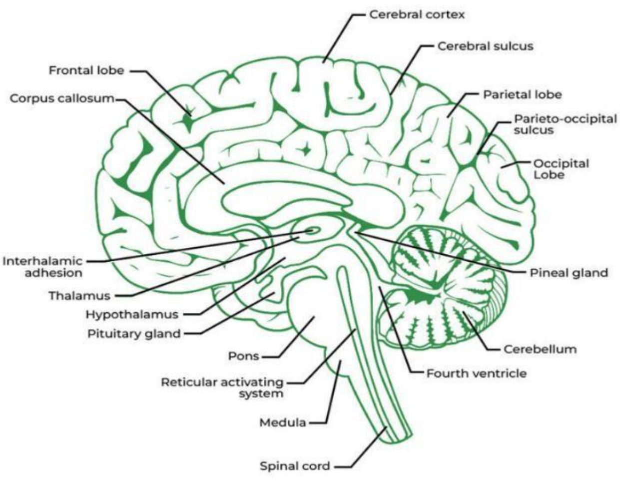


Fig.1: Basic Structure of human brain

Brain tumors are divided into two types: primary (benign tumors) and secondary (malignant tumors).A benign tumor is a type of cell that grows slowly in the brain, while gliomas are another type of brain tumor. It comes from non-neuronal brain cells called astrocytes. Primary tumors are less aggressive, but they put a lot of pressure on the brain, which causes it to stop working properly [6]. Secondary tumors are more aggressive and spread more quickly into surrounding tissue. Secondary brain tumors develop from other parts of the body. These types of tumors have a metastatic cancer cell in the body that has spread to various parts of the body, such as the brain and lungs. Secondary brain tumors are highly malignant. Secondary brain tumors are primarily caused by cancers of the lungs, kidneys, and bladder.

C. MAGNETIC RESONANCE IMAGING (MRI):

Raymond V. Damadian created the first magnetic image in 1969. The first MRI image of the human body, as well as the most perfect technique, were invented in 1977. MRI allows us to see the details of the brain's internal structure and thus observe the various types of tissues in the human body. MRI images are of higher quality when compared to other medical imaging techniques such as X-rays and computer tomography.[8]. MRI is a useful technique for identifying brain tumors in the human body. There are different images of MRI for mapping tumor-induced change, including T1 weighted, T2 weighted, and FLAIR (fluid attenuated inversion recovery) weighted shown in figure.

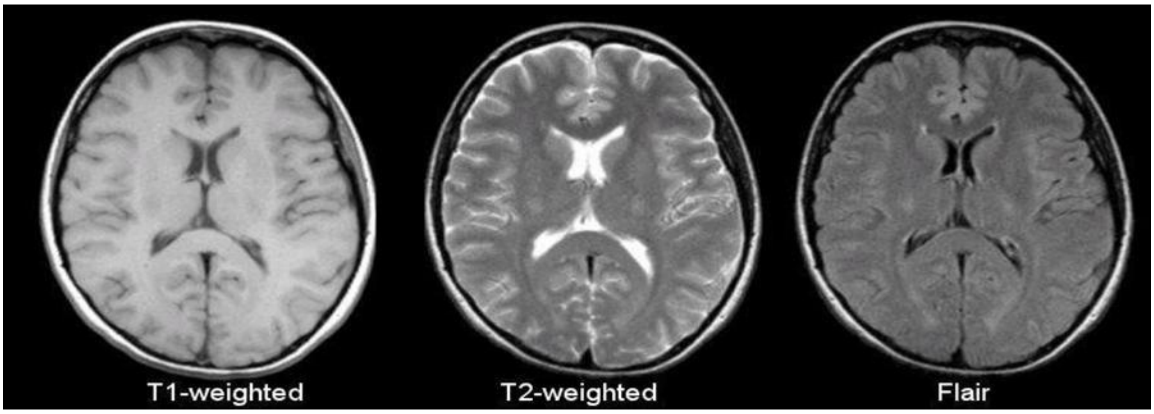


Fig 2: T1, T2 and Flair image

The most common MRI sequences are T1 and T2 weighted. In T1 weighted, only one tissue type is bright FAT, whereas T2 weighted has two tissue types: bright FAT and water. In T1 weighted, the repetition time (TR) is short; in T2 weighted, the TE and TR are both long. The pulse sequence parameters are TE and TR, which stand for repetition time and time to echo, and can be measured in milliseconds (ms) [9]. The echo time represents time from the center of the RF pulse to the center of the echo, and TR is the length of time between the TE repeating series of pulse and echo, as shown in figure.

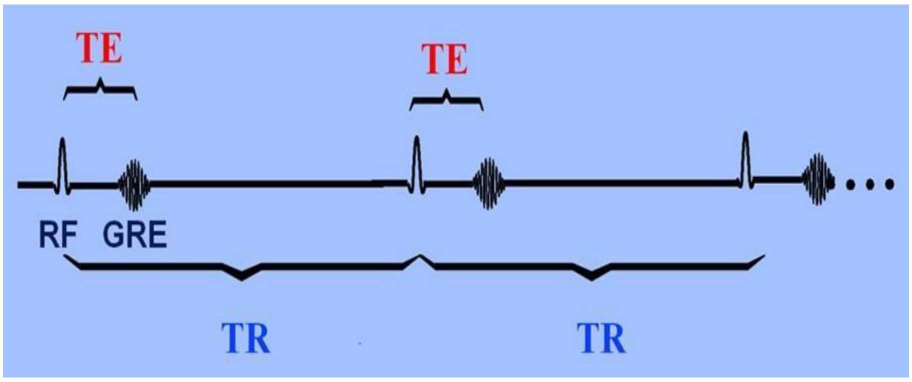


Fig. 3: Graph of TE and TR

The third most commonly used sequence in FLAIR. The Flair sequence is almost identical to the T2-weighted image. The only difference is that TE and TR times are extremely long. The approximate TR and TE times are shown in the table.

	TR (msec)	TE (msec)
T1-Weighted (short TR and TE)	500	14
T2-Weighted (long TR and TE)	4000	90
Flair (very long TR and TE	9000	114

Fig.4: Table of TR and TE time

D.APPLICATION:

• The primary goal of the applications is tumor identification.
• The application's main goal is to provide prompt treatment and protect vulnerable individuals.
• This application benefits both doctors and patients.
• Manual identification is slower, but more accurate and efficient for users. This application is designed to address these issues.
• The application is user-friendly.

E.OBJECTIVE:

• Provide doctors with effective software to identify tumors and their causes.
• Save patients' time.
• Provide appropriate solutions at early stages.
• Receive timely consultation.

F.MOTIVATION:

The primary motivation for brain tumor detection is to not only detect but also classify different types of tumors. So it can be useful in situations where we need to know if a tumor is positive or negative; it can detect tumors from images and return whether the tumor is positive or not. This project deals with a system that uses computer-based procedures to detect tumor blocks and classify the type of tumor using the Convolution Neural Network Algorithm for MRI images of different patients.

II. JEXISTING WORK & PROPOSED WORKFLOW

A.OVERVIEW OF EXISTING WORK:

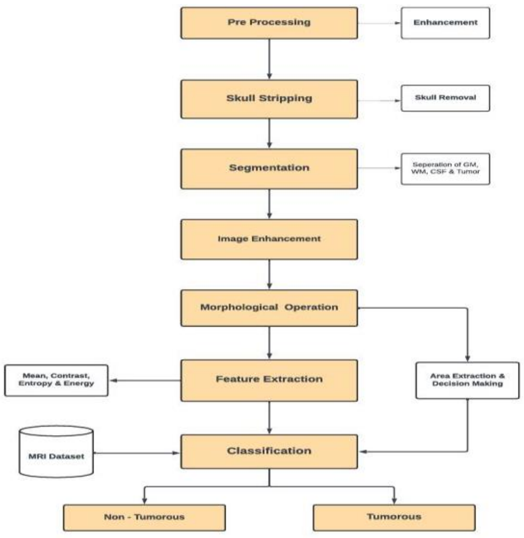


Fig.5.Existing work flow of brain tumor detection. [12]

• In the first stage, there is a computer based procedures to detect tumor blocks and classify the type of tumor using Artificial Neural Network Algorithm for MRI images of different patients.
• The second stage involves the use of different image processing techniques such as histogram equalization, image segmentation, image enhancement, morphological operations and feature extraction are used for brain tumor detection in the MRI images for the cancer-affected patients.
• This work is introduced one automatic brain tumor detection method to increase the accuracy and decrease the diagnosis time.
• **Image Preprocessing**: The system's input is MRI scanned images containing noise. The primary objective is to eliminate this noise using a high pass filter, as outlined in the system flow for noise removal and preprocessing.
• **Segmentation**: Region growing is a simple region-based image segmentation technique classified as a pixel-based approach due to the selection of initial seed points.
• **Morphological operation**: This operation is utilized to extract boundary areas in brain images. It involves rearranging pixel value orders rather than mathematical values, making it suitable for binary images. Dilation and erosion are fundamental operations in morphology. Dilation adds pixels to the object's boundary region, while erosion removes pixels from the boundary region.
• **Feature Extraction**: Used for edge detection in images, this process gathers high-level image information such as shape, texture, color, and contrast.
• **Connected component labeling**: After recognizing connected components of an image, every set of connected pixels having same gray-level values are assigned the same unique region label.
• **Tumor Identification**: In this phase, features are extracted from a previously collected dataset of brain MRIs for comparison in a knowledge base.

B .PROPOSED WORKFLOW:

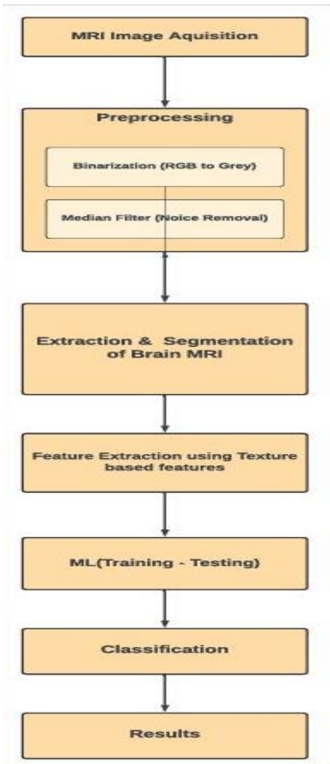


Fig. 6.Proposed work flow of brain tumor detection

The proposed system consists of five main modules: Dataset, Pre-processing, Data Splitting, CNN Model Building, Deep Neural Network Training for epochs, and Classification.

In the Dataset module, multiple MRI images are utilized, with one selected as input image. During Pre-processing, the image is labeled and resized. Data Splitting involves allocating 80% of the images as Training Data and 20% as Testing Data. Subsequently, the CNN model is constructed and trained for epochs through the Deep Neural Network. Finally, the images are classified as "yes" for positive tumors and "no" for negative ones.

.

C.Working of CNN model:

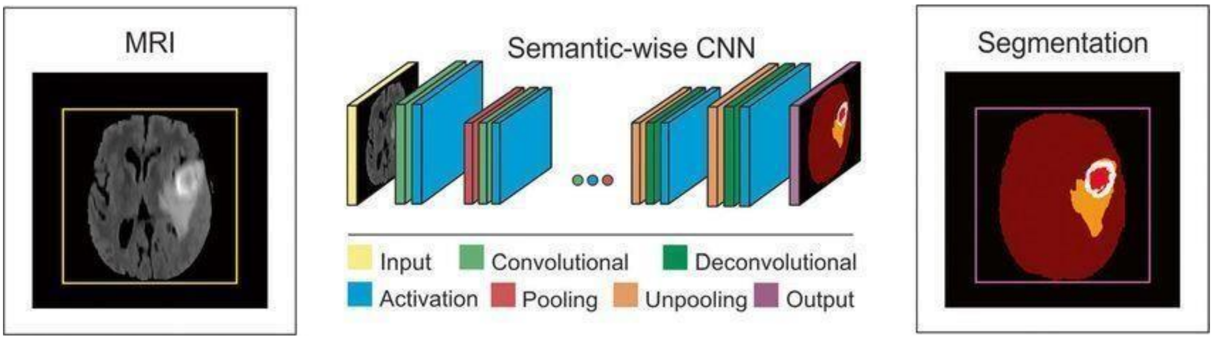


Fig.7.Working of CNN model for brain tumor detection [14]

Layer of CNN model:

- Convolution 2D
- MAX Poolig2D
- Dropout
- Flatten
- Dense
- Activation

Convolution 2D: In the Convolution 2D extract the featured from input image. It given the output in matrix form.
MAX Poolig2D: In the MAX polling 2D it take the largest element from rectified feature map.
Dropout: Dropout is randomly selected neurons are ignored during training.
Flatten: Flatten feed output into fully connected layer. It gives data in list form.
Dense: A Linear operation in which every input is connected to every output by weight. It followed by nonlinear activation function.
Activation: It used Sigmoid function and predict the probability 0 and 1.
In the compile model we used binary cross entropy because we have two layers 0 and 1.
We used Adam optimizer in compile model.
Adam:-Adaptive moment estimation. It used for non convex optimization problem like straight forward to implement.

- Computationally efficient
- Little memory requirement

D. Working of VGG19 model:

Transfer learning is a knowledge- sharing method that reduces the size of the training data, the time and the computational costs when building deep learning models. Transfer learning helps to transfer the learning of a pre-trained model to a new model. Transfer learning has been used in various applications, such as tumor classification, software defect prediction, activity recognition and sentiment classification. In this, the performance of the proposed Deep CNN model has been compared with popular transfer learning approach VGG19.

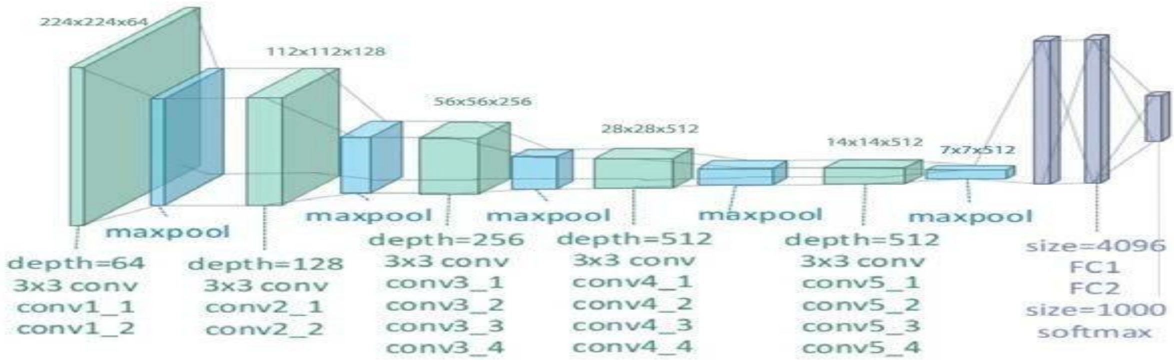


Fig.8.Working of VGG19 model for brain tumor detection & layered architecture

VGG19 is a convolutional neural network. The input to the first convolution layer has a fixed size of 224 x 224 RGB image. The image goes through a series of convolutional layers with 3x3 filters to capture left/right, up/down, and center features. Additionally, 1x1 convolution filters are used for linear transformations of input channels.

Following the convolutional layers are three Fully-Connected (FC) layers with varying depths in different architectures. The first two FC layers have 4096 channels each, while the third layer is responsible for 1000-way ILSVRC classification with 1000 channels representing each class.

All hidden layers utilize rectification (ReLU) nonlinearity. It is important to note that most networks do not incorporate Local Response Normalization (LRN) due to its minimal impact on performance and its negative effects on memory consumption and computation time

III. DATASET IMPLEMENTATION AND RESULT

A.DATASET DETAIL:

The dataset has 200 images with different types of tumor.

• Out which 150 has tumor and 50 has no tumor

• Since the data is too low so we will created new images using Data augmentation.

B. TOOLS & TECHNOLOGY USED:

• Python: Python was the language of selection for this project. This was a straightforward call for many reasons.

• Python has a vast community and strong support on platforms like Stack Overflow. It is one of the most commonly used languages, ensuring quick access to solutions.

• Python offers powerful tools for scientific computing, such as NumPy, Pandas, and SciPy, which are widely available and well-documented. These tools can significantly simplify programming and speed up the iteration process.

• Python's forgiving nature allows for programming that closely resembles pseudo code. This is particularly useful when implementing pseudo-code from academic publications. However, Python is not without faults; it is dynamically typed and packages are sometimes known for Duck typing. This can lead to confusion when a method returns unexpected outputs, making it difficult to learn and implement new libraries.

• **Jupyter Notebook**: Jupyter Notebook is a popular open-source web application used for creating and sharing documents that include live code, equations, visualizations, and text. It is commonly used for tasks such as data cleaning, statistical modeling, and machine learning.

• **Noise Removal and Sharpening**: Unwanted elements in the data can be removed using filters, and images can be sharpened. Grayscale images are often used as input for this process.

• **Erosion and Dilation**: These operations are typically applied to binary images but can also be used with grayscale images, depending on the variant. The basic effect of these operators on binary images is erosion towards the boundaries of regions.
• **Negation**: Negation involves creating a negative image, where the lightest areas in the original image appear darkest and vice versa. This technique is commonly used in photography.
• **Subtraction**: Image subtraction involves taking the digital pixel values of one image and subtracting them from another. This process can, for example, help to isolate a white tumor from the rest of the image.
• **Threshold**: Thresholding is a method of segmenting images by converting grayscale images into binary images.

IV. RESULTS

A. MODEL BUILDING:

Load the VGG 19 model

```
base_model = VGG19(include_top=False, input_shape=(240,240,3))
base_model_layer_names = [layer.name for layer in base_model.layers]
base_model_layer_names
```

Fig 9. Consist of VGG 19 base model

Create a new model that includes the VGG 19 base model and additional layers of Classification

```
class_1 = Dense(4608, activation = 'relu')(flat)
drop_out = Dropout(0.2)(class_1)
class_2 = Dense(1152, activation = 'relu')(drop_out)
output = Dense(2, activation = 'softmax')(class_2)
```

Fig 10. Consist additional layers of classification of VGG 19 Model

B. MODEL COMPILATION:

```
# Compile the model with the Legacy optimizer
model_03.compile(loss='categorical_crossentropy', optimizer=sgd, metrics=['accuracy'])
```

Fig 11. Model Compilation

C. MODEL TRAINING:

```
history_03 = model_03.fit(train_generator, steps_per_epoch=10, epochs =10 , callbacks=[es,cp,lrr], validation_data=valid_gene
```

Fig 12. Training of the Model

D. TRAINED MODEL SUMMARY:

```
model_03.summary()

Model: "model_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_4 (InputLayer)        [(None, 240, 240, 3)]     0

 block1_conv1 (Conv2D)       (None, 240, 240, 64)      1792

 block1_conv2 (Conv2D)       (None, 240, 240, 64)      36928

 block1_pool (MaxPooling2D)  (None, 120, 120, 64)      0

 block2_conv1 (Conv2D)       (None, 120, 120, 128)     73856

 block2_conv2 (Conv2D)       (None, 120, 120, 128)     147584

 block2_pool (MaxPooling2D)  (None, 60, 60, 128)       0

 block3_conv1 (Conv2D)       (None, 60, 60, 256)       295168

 block3_conv2 (Conv2D)       (None, 60, 60, 256)       590080

 block3_conv3 (Conv2D)       (None, 60, 60, 256)       590080

 block3_conv4 (Conv2D)       (None, 60, 60, 256)       590080

 block3_pool (MaxPooling2D)  (None, 30, 30, 256)       0

 block4_conv1 (Conv2D)       (None, 30, 30, 512)       1180160

 block4_conv2 (Conv2D)       (None, 30, 30, 512)       2359808

 block4_conv3 (Conv2D)       (None, 30, 30, 512)       2359808

 block4_conv4 (Conv2D)       (None, 30, 30, 512)       2359808

 block4_pool (MaxPooling2D)  (None, 15, 15, 512)       0

 block5_conv1 (Conv2D)       (None, 15, 15, 512)       2359808

 block5_conv2 (Conv2D)       (None, 15, 15, 512)       2359808

 block5_conv3 (Conv2D)       (None, 15, 15, 512)       2359808

 block5_conv4 (Conv2D)       (None, 15, 15, 512)       2359808

 block5_pool (MaxPooling2D)  (None, 7, 7, 512)         0

 flatten_2 (Flatten)         (None, 25088)             0

 dense_6 (Dense)             (None, 4608)              115610112

 dropout_2 (Dropout)         (None, 4608)              0

 dense_7 (Dense)             (None, 1152)              5309568

 dense_8 (Dense)             (None, 2)                 2306

=================================================================
Total params: 140946370 (537.67 MB)
Trainable params: 140946370 (537.67 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Fig 13. Trained Model Summary

E. BEST TRAINED MODEL EPOCH DETAILS:

```
s are: loss,accuracy,val_loss,val_accuracy,lr
10/10 [==============================] - 203s 21s/step - loss: 0.6317 - accuracy: 0.6406 - val_loss: 0.5818 - val_accuracy:
0.7217 - lr: 1.0000e-04
Epoch 2/10
10/10 [==============================] - ETA: 0s - loss: 0.5870 - accuracy: 0.7125
Epoch 2: val_loss improved from 0.58180 to 0.56435, saving model to model.h5
WARNING:tensorflow:Learning rate reduction is conditioned on metric `val_accuarcy` which is not available. Available metric
s are: loss,accuracy,val_loss,val_accuracy,lr
10/10 [==============================] - 190s 19s/step - loss: 0.5870 - accuracy: 0.7125 - val_loss: 0.5643 - val_accuracy:
0.6958 - lr: 1.0000e-04
Epoch 3/10
10/10 [==============================] - ETA: 0s - loss: 0.5272 - accuracy: 0.7594
Epoch 3: val_loss did not improve from 0.56435
WARNING:tensorflow:Learning rate reduction is conditioned on metric `val_accuarcy` which is not available. Available metric
s are: loss,accuracy,val_loss,val_accuracy,lr
10/10 [==============================] - 190s 19s/step - loss: 0.5272 - accuracy: 0.7594 - val_loss: 0.5729 - val_accuracy:
0.7282 - lr: 1.0000e-04
Epoch 4/10
10/10 [==============================] - ETA: 0s - loss: 0.6208 - accuracy: 0.6451
Epoch 4: val_loss improved from 0.56435 to 0.55123, saving model to model.h5
WARNING:tensorflow:Learning rate reduction is conditioned on metric `val_accuarcy` which is not available. Available metric
s are: loss,accuracy,val_loss,val_accuracy,lr
10/10 [==============================] - 182s 19s/step - loss: 0.6208 - accuracy: 0.6451 - val_loss: 0.5512 - val_accuracy:
0.7023 - lr: 1.0000e-04
Epoch 5/10
10/10 [==============================] - ETA: 0s - loss: 0.5460 - accuracy: 0.7219
Epoch 5: val_loss did not improve from 0.55123
WARNING:tensorflow:Learning rate reduction is conditioned on metric `val_accuarcy` which is not available. Available metric
s are: loss,accuracy,val_loss,val_accuracy,lr
10/10 [==============================] - 190s 19s/step - loss: 0.5460 - accuracy: 0.7219 - val_loss: 0.5640 - val_accuracy:
0.6958 - lr: 1.0000e-04
Epoch 6/10
10/10 [==============================] - ETA: 0s - loss: 0.5244 - accuracy: 0.7375
Epoch 6: val_loss did not improve from 0.55123
WARNING:tensorflow:Learning rate reduction is conditioned on metric `val_accuarcy` which is not available. Available metric
s are: loss,accuracy,val_loss,val_accuracy,lr
10/10 [==============================] - 190s 19s/step - loss: 0.5244 - accuracy: 0.7375 - val_loss: 0.5681 - val_accuracy:
0.6699 - lr: 1.0000e-04
Epoch 7/10
10/10 [==============================] - ETA: 0s - loss: 0.4991 - accuracy: 0.7713
Epoch 7: val_loss improved from 0.55123 to 0.52605, saving model to model.h5
WARNING:tensorflow:Learning rate reduction is conditioned on metric `val_accuarcy` which is not available. Available metric
s are: loss,accuracy,val_loss,val_accuracy,lr
10/10 [==============================] - 180s 18s/step - loss: 0.4991 - accuracy: 0.7713 - val_loss: 0.5261 - val_accuracy:
0.7184 - lr: 1.0000e-04
Epoch 8/10
10/10 [==============================] - ETA: 0s - loss: 0.4909 - accuracy: 0.7719
Epoch 8: val_loss improved from 0.52605 to 0.50004, saving model to model.h5
WARNING:tensorflow:Learning rate reduction is conditioned on metric `val_accuarcy` which is not available. Available metric
s are: loss,accuracy,val_loss,val_accuracy,lr
10/10 [==============================] - 192s 20s/step - loss: 0.4909 - accuracy: 0.7719 - val_loss: 0.5000 - val_accuracy:
0.7443 - lr: 1.0000e-04
Epoch 9/10
10/10 [==============================] - ETA: 0s - loss: 0.4755 - accuracy: 0.7850
Epoch 9: val_loss did not improve from 0.50004
WARNING:tensorflow:Learning rate reduction is conditioned on metric `val_accuarcy` which is not available. Available metric
s are: loss,accuracy,val_loss,val_accuracy,lr
10/10 [==============================] - 182s 18s/step - loss: 0.4755 - accuracy: 0.7850 - val_loss: 0.5609 - val_accuracy:
0.6796 - lr: 1.0000e-04
Epoch 10/10
10/10 [==============================] - ETA: 0s - loss: 0.4476 - accuracy: 0.8062
Epoch 10: val_loss improved from 0.50004 to 0.46943, saving model to model.h5
WARNING:tensorflow:Learning rate reduction is conditioned on metric `val_accuarcy` which is not available. Available metric
s are: loss,accuracy,val_loss,val_accuracy,lr
10/10 [==============================] - 195s 20s/step - loss: 0.4476 - accuracy: 0.8062 - val_loss: 0.4694 - val_accuracy:
0.7735 - lr: 1.0000e-04
```

Fig 14. Epochs Trained

F. ACCURACY:

In this experiment, a pre-trained VGG19 convolutional neural network (CNN) was employed for brain tumor classification. After training the model for 10 epochs on the data, an accuracy of 80% was achieved. While increasing the number of epochs might lead to further accuracy improvement, it's important to evaluate the model's performance against other architectures to determine if VGG19 offers the optimal solution for this specific task.

G. PLOT PERFORMANCE:

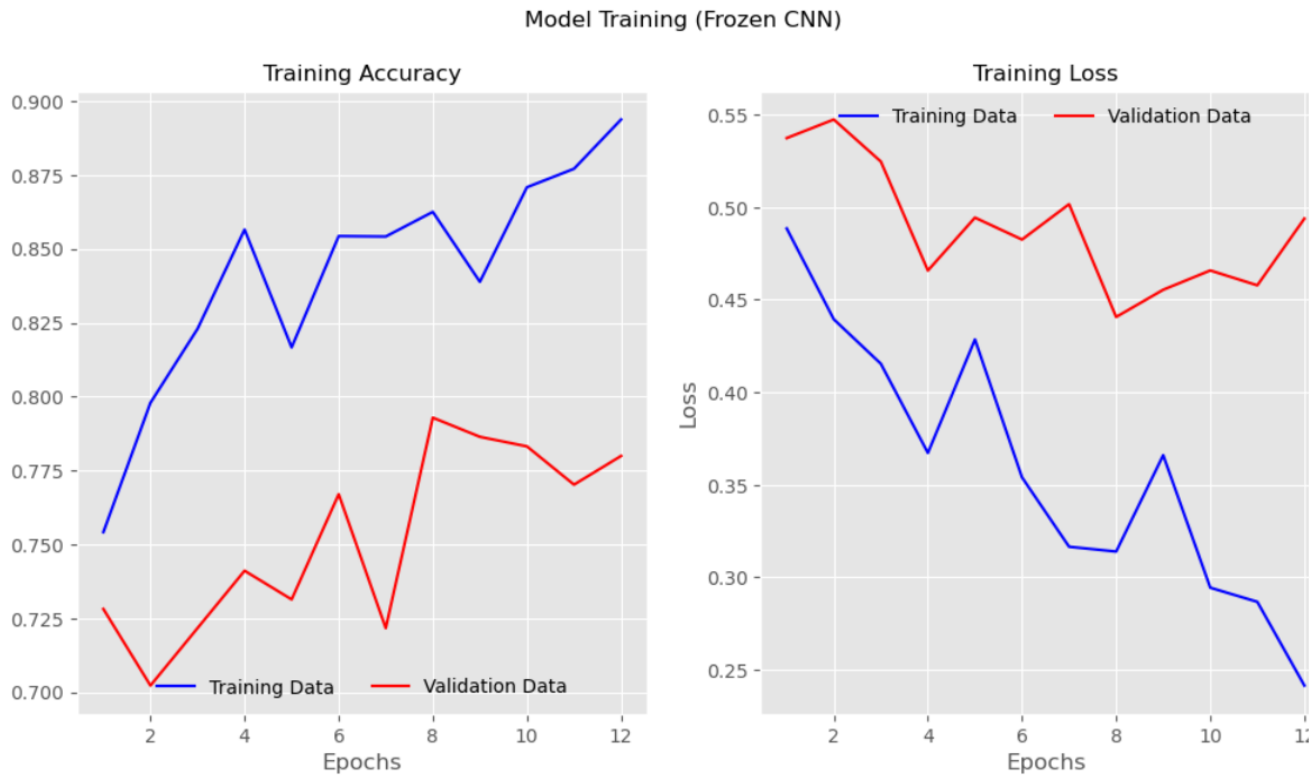


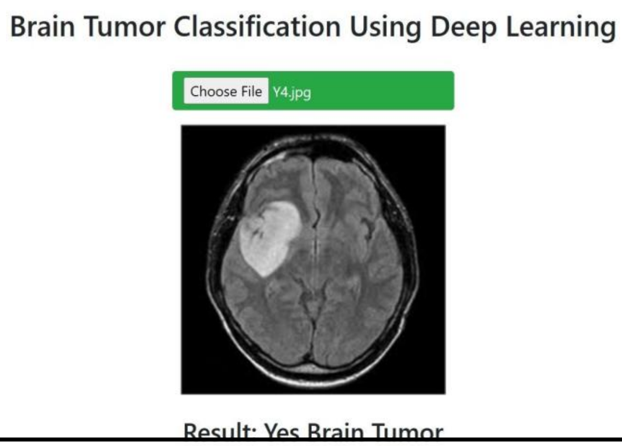
Fig 15. Comparison Graph of the Best Trained Model

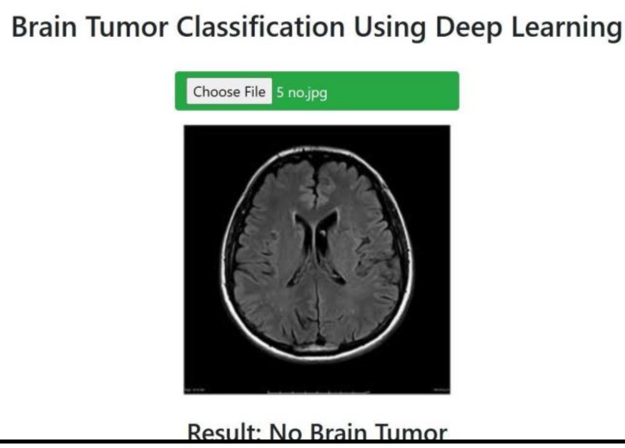
V. CONCLUSION

The developed Brain Tumor Detection system was deployed using the Python Flask integrated model with React web app, allowing for easy integration and accessibility. Users can upload MRI scans through a web interface, and the system provides real-time predictions regarding the presence of tumors.

The deployed system demonstrated promising performance in detecting brain tumors, achieving high accuracy and robustness in real-world scenarios. The model's ability to accurately classify tumor and non-tumor images signifies its potential as a valuable diagnostic tool for healthcare professionals.

In brain tumor detection, we have studied feature-based existing work, including image processing techniques such as image pre-processing, image segmentation feature extraction, and classification. Furthermore, we have explored deep learning techniques such as CNN and VGG19. In this system, we detect the presence of a tumor. The model returns "yes" if the tumor is present, otherwise it returns "no." We have compared CNN with the VGG19 model, and the results show that VGG19 is more accurate than CNN. However, no task is perfect, and there is always room for improvement in this field. Through this work, I have gained valuable knowledge and insights in the field of development.





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CONTRIBUTION

Aarnab Dutta (2105343)

Abstract:
This report presents a system for brain tumor detection using advanced techniques like Convolutional Neural Networks (CNN) and VGG19 transfer learning models. The system aims to accurately identify tumors from MRI scans, providing timely diagnosis and treatment planning. A comprehensive dataset of brain MRI images is utilized, with preprocessing, data splitting, and model training stages. Comparative analyses demonstrate the superior performance of the VGG19 model over the CNN model in terms of tumor detection accuracy. The developed system shows promise as an efficient diagnostic tool for medical professionals, offering automation and reliability in brain tumor identification.

Individual contribution in code and findings

- Implemented the Convolutional Neural Network (CNN) model for brain tumor detection.
- Optimized the model's hyperparameters to improve accuracy and performance.
- Analyzed the results and compared the CNN model's performance with the VGG19 transfer learning model.

Individual contribution to project report analysis

- Wrote the sections on the Convolutional Neural Network (CNN) model's working principle and implementation details.
- Analyzed and presented the CNN model's performance results in the report.
- Contributed to the comparison analysis between the CNN and VGG19 models.

Individual contribution for project presentation and demonstration

- Prepared and delivered the presentation slides on the CNN model's implementation and results.
- Conducted live demonstrations of the brain tumor detection system using the CNN model.
- Answered questions from the audience related to the CNN model's performance and limitations.

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Abhishek Ranjan (2105348)

Abstract:

This report presents a system for brain tumor detection using advanced techniques like Convolutional Neural Networks (CNN) and VGG19 transfer learning models. The system aims to accurately identify tumors from MRI scans, providing timely diagnosis and treatment planning. A comprehensive dataset of brain MRI images is utilized, with preprocessing, data splitting, and model training stages. Comparative analyses demonstrate the superior performance of the VGG19 model over the CNN model in terms of tumor detection accuracy. The developed system shows promise as an efficient diagnostic tool for medical professionals, offering automation and reliability in brain tumor identification.

Individual contribution in code and findings

- Worked on data preprocessing and augmentation techniques to increase the dataset size.
- Implemented the VGG19 transfer learning model and fine-tuned it for brain tumor detection.
- Conducted experiments and analyzed the performance of the VGG19 model on the test dataset.

Individual contribution to project report analysis

- Documented the VGG19 transfer learning model's architecture and working principle.
- Prepared the sections on dataset details, tools, and technologies used in the project.
- Analyzed and presented the VGG19 model's performance results in the report.

Individual contribution for project presentation and demonstration

- Presented the VGG19 transfer learning model's architecture, working principle, and implementation details.
- Demonstrated the system's performance using the VGG19 model on test MRI scans.
- Addressed questions from the audience regarding the transfer learning approach and its advantages.

Full Signature of Supervisor Full Signature of Student

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Ravi Raj Shrivastava (2105816)

Abstract:

This report presents a system for brain tumor detection using advanced techniques like Convolutional Neural Networks (CNN) and VGG19 transfer learning models. The system aims to accurately identify tumors from MRI scans, providing timely diagnosis and treatment planning. A comprehensive dataset of brain MRI images is utilized, with preprocessing, data splitting, and model training stages. Comparative analyses demonstrate the superior performance of the VGG19 model over the CNN model in terms of tumor detection accuracy. The developed system shows promise as an efficient diagnostic tool for medical professionals, offering automation and reliability in brain tumor identification.

Individual contribution in code and findings

- Developed the user interface for the brain tumor detection system using web technologies (e.g., Flask).
- Integrated the CNN and VGG19 models with the web application for seamless user interaction.
- Implemented functionality for uploading MRI scans and displaying the prediction results.

Individual contribution to project report analysis

- Wrote the sections on the project's motivation, objectives, and applications.
- Documented the web application's implementation details and user interface features.
- Contributed to the report's introduction and background information on brain tumors and MRI.

Individual contribution for project presentation and demonstration

- Presented the web application's user interface and functionalities for brain tumor detection.
- Conducted live demonstrations of the web application, showcasing the upload and prediction process.
- Addressed queries from the audience related to the user experience and potential real-world applications.

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Shivam Singh (21051732)

Abstract:

This report presents a system for brain tumor detection using advanced techniques like Convolutional Neural Networks (CNN) and VGG19 transfer learning models. The system aims to accurately identify tumors from MRI scans, providing timely diagnosis and treatment planning. A comprehensive dataset of brain MRI images is utilized, with preprocessing, data splitting, and model training stages. Comparative analyses demonstrate the superior performance of the VGG19 model over the CNN model in terms of tumor detection accuracy. The developed system shows promise as an efficient diagnostic tool for medical professionals, offering automation and reliability in brain tumor identification.

Individual contribution in code and findings

- Explored different image processing techniques for enhancing MRI scan quality.
- Implemented noise removal, sharpening, and segmentation algorithms for preprocessing the images.
- Contributed to the evaluation of the models' performance on different preprocessing techniques.

Individual contribution to project report analysis

- Documented the image pre-processing techniques used in the project, including noise removal and sharpening.
- Wrote the sections on existing work and proposed workflow for brain tumor detection.
- Contributed to the report's conclusion and future work recommendations.

Individual contribution for project presentation and demonstration

- Presented the image preprocessing techniques employed in the project, including noise removal and segmentation.
- Demonstrated the impact of preprocessing on the models' performance using sample MRI scans.
- Answered questions from the audience regarding the preprocessing methods and their importance.

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Sai Sanket Bal(21051164)

Abstract:

This report presents a system for brain tumor detection using advanced techniques like Convolutional Neural Networks (CNN) and VGG19 transfer learning models. The system aims to accurately identify tumors from MRI scans, providing timely diagnosis and treatment planning. A comprehensive dataset of brain MRI images is utilized, with preprocessing, data splitting, and model training stages. Comparative analyses demonstrate the superior performance of the VGG19 model over the CNN model in terms of tumor detection accuracy. The developed system shows promise as an efficient diagnostic tool for medical professionals, offering automation and reliability in brain tumor identification.

Individual contribution in code and findings

- Researched and studied existing brain tumor detection methods and algorithms.
- Conducted a literature review on deep learning techniques for medical image analysis.
- Assisted in the development and testing of the CNN and VGG19 models.

Individual contribution to project report analysis

- Prepared the abstract and keywords section, summarizing the project's goals and key aspects.
- Wrote the sections on brain anatomy, MRI imaging, and the importance of brain tumor detection.
- Contributed to the project's literature review and analysis of existing work.

Individual contribution for project presentation and demonstration

- Delivered an overview presentation, introducing the project's background, motivation, and objectives.
- Presented the literature review and analysis of existing brain tumor detection methods.
- Addressed general questions from the audience and provided concluding remarks.

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Vinnamala Sai Sujith (2105339)

Abstract:

This report presents a system for brain tumor detection using advanced techniques like Convolutional Neural Networks (CNN) and VGG19 transfer learning models. The system aims to accurately identify tumors from MRI scans, providing timely diagnosis and treatment planning. A comprehensive dataset of brain MRI images is utilized, with preprocessing, data splitting, and model training stages. Comparative analyses demonstrate the superior performance of the VGG19 model over the CNN model in terms of tumor detection accuracy. The developed system shows promise as an efficient diagnostic tool for medical professionals, offering automation and reliability in brain tumor identification.

Individual contribution in code and findings

- Designed and implemented the model evaluation metrics, including accuracy, precision, recall, and F1 score.
- Performed cross-validation to ensure the robustness of the models.
- Developed scripts for visualizing model performance metrics such as confusion matrices and ROC curves.

Individual contribution to project report analysis

- Documented the evaluation techniques and the rationale behind choosing specific metrics.
- Wrote the sections on experimental results and their interpretation, supported by data visualization.
- Contributed to the discussion on the challenges and limitations of the proposed system.
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Individual contribution for project presentation and demonstration

- Presented the statistical analysis of the models' performance and their practical implications.
- Demonstrated the evaluation process using real-time data and showcased the reliability of predictions.
- Addressed questions from the audience on model reliability and suggestions for future improvements.

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