Cerebral Watch: Tumor Monitoring

Aarnab Dutta[1], Abhishek Ranjan[2], Ravi Raj Shrivastava[3], Sai Sanket Bal[4],Shivam Singh[5], Vinnamala Sai Sujith[6],
2105343@kiit.ac.in, 2105348@kiit.ac.in, 2105816@kiit.ac.in, 21051164@kiit.ac.in, 21051732@kiit.ac.in, 2105339@kiit.ac.in

School of Computer Engineering, KIIT Deemed to Be University, Bhubaneswar -751024, Odisha, India

ABSTRACT

Currently, tumors rank as the second most prevalent cause of cancer, presenting a considerable risk to numerous patients [1, 3]. Within the medical sphere, there exists a pressing demand for a swift, automated, efficient, and dependable approach to tumor detection, particularly concerning brain tumors. Accurate tumor detection is imperative for effective treatment, ensuring patient safety. This tool employs diverse image processing techniques. Physicians rely on this tool to administer suitable treatment, thereby preserving the lives of many afflicted with tumors. Fundamentally, a tumor manifests as an abnormal proliferation of cells that proliferate uncontrollably. In instances of brain tumors, this abnormal growth disrupts the supply of essential nutrients to healthy cells and tissues, resulting in brain dysfunction [4]. Presently, physicians manually scrutinize MRI images to pinpoint the presence and location of brain tumors, a method vulnerable to inaccuracies and time constraints. Deep Learning frameworks such as Convolutional Neural Networks (CNN) and VGG 19 Transfer Learning offer a solution by discerning the presence of tumors in images. Upon detection, the output categorizes the presence of a tumor as "yes," and its absence as "no."

Keywords: Brain tumors, MRI, Convolution Neural Network, VGG19
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I. INTRODUCTION

A. SYSTEM FOR IDENTIFYING BRAIN TUMORS:

The body of humans comprises numerous organs, among which the brain holds utmost significance. Brain tumors commonly disrupt brain function. Essentially, a tumor results from the abnormal growth of cells, which proliferate uncontrollably. This growth pattern leads to the depletion of nutrients necessary for healthy cells and tissues, eventually causing brain dysfunction. Presently, physicians depend on manual examination of patients' MRI scans to determine the size and location of brain tumors, a method prone to inaccuracy and time consumption. Brain cancer is a severe ailment claiming many lives. Thankfully, there exists a system for early detection and classification of brain tumors, facilitating swift diagnosis. Cancer classification poses a notable challenge in clinical diagnosis. This project specifically focuses on implementing a computer-based system utilizing Convolution Neural Network Algorithm for detecting tumor masses and classifying various types of brain tumors based on MRI images from diverse patients [2]. Various image processing methods, including segmentation, enhancement, and feature extraction, are employed to identify brain tumors in MRI scans of cancer patients. Brain tumor detection through image processing involves four main stages: preprocessing of images, segmentation, extracting features, and classification.To enhance the accuracy of detecting and categorizing brain tumors in MRI images, a combination of image processing and neural network techniques is applied [5].

B. AN INTRODUCTION TO BRAIN AND BRAIN TUMORS:

The human neurological system relies heavily on the brain, nestled within the protective confines of the skull. Functioning as the body's command center, it meticulously regulates all physiological processes, ensuring adaptability to diverse environmental challenges [2]. Beyond its regulatory role, the brain empowers individuals to engage in actions and articulate thoughts and emotions effectively. Within this segment, we embark on an exploration of the brain's intricate architecture and its profound capacity to grasp fundamental concepts.

At the core of the human neurological system lies the brain, situated within the head and shielded by the skull. Chief among its responsibilities is the oversight of bodily functions, allowing for adaptation and resilience amidst varying environmental pressures. Moreover, the human brain serves as a conduit for the expression of thoughts and emotions, enabling effective communication and interaction [7]. This section embarks on a journey to uncover the complexities of the brain's structure and its integral role in comprehending essential concepts, shedding light on its remarkable capabilities and contributions to human cognition and behavior.

C. MAGNETIC RESONANCE IMAGING (MRI):

Raymond V. Damadian transformed medical imaging with his pioneering work, creating the first magnetic image in 1969 and achieving another milestone in 1977 with the first MRI image of the human body. MRI remains a leading-edge technique for visualizing internal structures and discerning various tissues within the body, offering superior quality compared to X-rays and computed tomography. MRI excels particularly in detecting brain tumors, utilizing diverse MRI sequences like T1 weighted, T2 weighted, and FLAIR (fluid attenuated inversion recovery) weighted images.

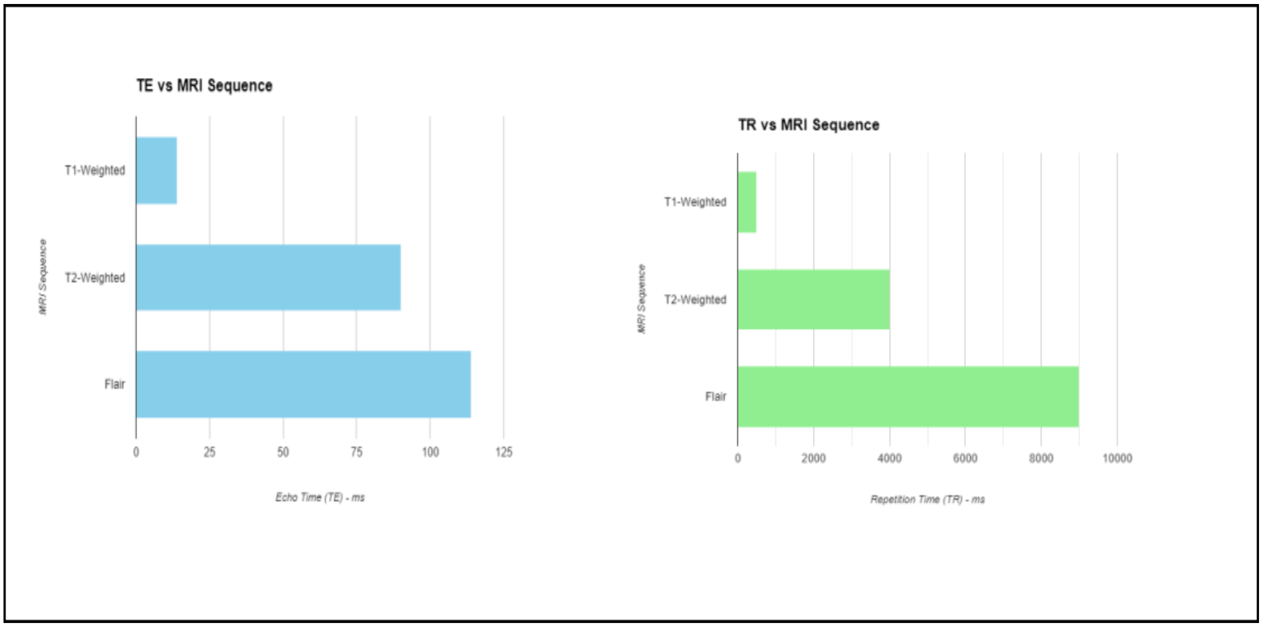

Fig. 1: Graph showing the TE and TR time for different MRI sequences

The T1 and T2 weighted sequences are the most prevalent MRI sequences. In T1 weighted sequences, fat appears bright, while T2 weighted sequences reveal both fat and water as bright tissues [8]. T1 sequences have short repetition times (TR), whereas T2 sequences feature long TR and time to echo (TE). These parameters, measured in milliseconds (ms), delineate the time from the RF pulse to the echo center (TE) and the duration between pulse and echo series (TR).

FLAIR sequences, ranking third in usage, closely resemble T2-weighted images but with notably prolonged TE and TR times, significantly extending their durations.

MRI Sequence	TR (msec)	TE (msec)
T1-Weighted	500	14

T2-Weighted	**4000**	**90**
Flair	**9000**	**114**

Fig. 2: Table of TR and TE time

D. APPLICATION:

• The primary function of these applications is tumor detection.
• The core purpose of the application is to ensure timely treatment and protect vulnerable individuals, offering benefits to both medical practitioners and patients.
• While manual identification may be slower, it proves to be more precise and effective for users.
• This application has been designed to address these challenges.
• The application features a user-friendly interface.

E. OBJECTIVE:

• Develop robust software tools for physicians to accurately detect tumors and ascertain their root causes.
• This groundbreaking technology not only saves patients crucial time but also ensures prompt delivery of appropriate solutions at the initial stages of diagnosis.
• By employing this advanced software, doctors can provide timely consultations, resulting in enhanced outcomes and more streamlined treatment strategies.

F. MOTIVATION:

The primary aim of brain tumor detection is not only to identify their presence but also to categorize them based on their types, especially in situations where distinguishing between malignant and benign tumors is critical. Through image analysis, the proposed system can effectively identify tumors and offer insights into their nature. The project focuses on utilizing computer-based methodologies, particularly the Convolutional Neural Network Algorithm, to detect tumor masses and classify them using MRI images from various patients.

II. EXISTING WORK AND SUGGESTED PROCESS PLAN

A. REVIEW OF PREVIOUS STUDIES:

Initially, automated methods are used to detect tumor masses and determine their type through the use of an Artificial Neural Network Algorithm analyzing MRI images from different patients [9]. The subsequent stage involves various image processing methods including histogram equalization, image segmentation, image enhancement, morphological operations, and feature extraction [9]. These methods are implemented to identify brain tumors in MRI scans of patients diagnosed with cancer

Image Preprocessing: Image preprocessing is an essential step in the system. The input consists of MRI scanned images that may contain noise. The main objective is to eliminate this noise using a high pass filter, as described in the system flow for noise removal and preprocessing.

Segmentation: The process uses a region growing technique, a straightforward approach based on regions for segmenting images. This method falls under the pixel-based category because it involves choosing initial seed points.

Morphological Operation: This technique is used to identify boundary regions in brain images. Rather than manipulating mathematical values, it rearranges the order of pixel values, which makes it especially effective.

Feature Extraction: This approach is used to identify edges in images and extract key details like shape, texture, color, and contrast.

Connected component labeling: Upon identifying the connected components within an image,each grouping of connected pixels sharing identical gray-level values is assigned [13].

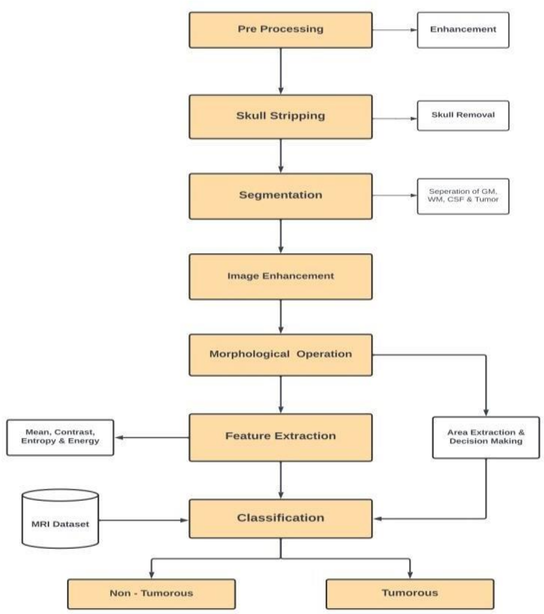

Fig. 3: Current workflow for detecting brain tumors

B. SUGGESTED PROCESS PLAN:

The proposed system consists of five main modules: Dataset, Pre-processing, Data Splitting, CNN Model Construction, Deep Neural Network Training for epochs, and Classification [11]. Within the Dataset module, several MRI images are utilized, with one selected as the input image. During Pre-processing, the image undergoes labeling and resizing. Data Splitting involves dividing 80% of the images for Training Data and 20% for Testing Data. Following this, the CNN model is built and trained for multiple epochs using the Deep Neural Network. Finally, the images are classified as "yes" for positive tumors and "no" for negative tumors.

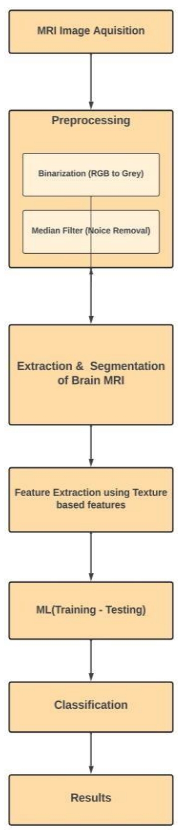

Fig. 4: Planned workflow for brain tumor identification

C. Functionality of CNN model:

The layers of the CNN model typically include:

- Convolutional Layer (Convolution 2D): This layer applies filters to input data to extract features [7].
- Pooling Layer(2D Max Pooling): It reduces the spatial dimensions of the convolved features, aiding in feature extraction.
- Activation Layer: Often following convolutional and pooling layers, this applies an activation function to introduce non-linearity.
- Fully Connected Layer: Also known as the dense layer, it connects every neuron from one layer to another.
- Output Layer: The final layer produces the output, often with a softmax activation for classification tasks.

Adam: Adam, known as Adaptive Moment Estimation, is frequently employed to tackle non-convex optimization challenges. Its implementation is simple, contributing to its widespread adoption. A notable benefit of Adam lies in its computational efficiency, facilitating expedited processing. Moreover, it exhibits a modest memory footprint, rendering it versatile across diverse applications.

D. Working of VGG-19 model:

Transfer learning is a method that facilitates knowledge transfer, decreasing the need for extensive training data, time, and computational resources in the development of deep learning models. It utilizes the insights from a pre-trained model to enhance a new model [4]. Transfer learning has been effectively utilized across various fields such as tumor classification, predicting software defects, recognizing activities, and classifying sentiments. In this research, the effectiveness of the proposed Deep CNN model is evaluated against the established transfer learning method known as VGG19. The VGG19 model is a form of convolutional neural network (CNN) that starts with an RGB image of 224 x 224 pixels. This image progresses through multiple convolutional layers that use 3x3 filters to identify features like edges, corners, and center points. Additionally, 1x1 convolution filters are used for linear transformations of the input channels.

After the convolutional layers, the VGG19 architecture includes three Fully-Connected (FC) layers. These FC layers exhibit varying depths in different arrangements. The initial two FC layers comprise 4096 channels each, while the third layer is dedicated to a 1000-way ILSVRC classification assignment, with 1000 channels representing individual classes [4].
All of the hidden layers in the VGG19 network use a rectified linear unit (ReLU) nonlinearity. It is worth noting that most networks do not include Local Response Normalization (LRN) because it has minimal impact on performance and can negatively affect memory consumption and computation time

III. IMPLEMENTATION AND OUTCOME OF THE DATASET

A. DETAILS OF THE DATASET

The dataset comprises 200 images depicting various tumor types.

- Out of which 150 has tumor and 50 has no tumor.
- Since the data is too low so we will create new images using Data Augmentation.

B. TOOLS AND TECHNOLOGICAL UTILIZATION:

The choice of Python as the primary language for this project was based on several factors. Python's extensive and vibrant community, along with robust support on platforms like Stack Overflow, was a primary consideration. Being one of the most popular programming languages, Python ensures rapid access to solutions and aid. Moreover, Python offers a rich array of tools for scientific computing, including NumPy, Pandas, and SciPy. which are not only widely accessible but also extensively documented. These tools greatly simplify the programming process and accelerate the iteration process. Another advantage of Python is its forgiving nature, allowing for coding that closely resembles pseudo code. This is especially beneficial when implementing pseudo code from academic publications. However, it is important to note that Python is not without its flaws. For instance, it is a dynamically typed language and its packages are sometimes associated with Duck typing. Consequently, this can lead to confusion when a method produces unexpected outputs, making it challenging to learn and utilize new libraries effectively.

Jupyter Notebook: was employed for the project: Jupyter Notebook, an open-source web application, is extensively utilized for creating and sharing documents incorporating live code, equations, visualizations, and text. Its popularity stems from its effectiveness in tasks like data cleaning, statistical modeling, and machine learning.

Noise Removal and Sharpening: An essential capability of Jupyter Notebook includes its capacity to eliminate distractions and improve image clarity.Filters are used to eliminate unwanted elements in the data, while sharpening techniques are applied to images. Grayscale images are commonly utilized as input for this

Erosion and Dilation: An essential capability of Jupyter Notebook includes its capacity to eliminate distractions and improve image clarity. Filters are used to eliminate unwanted elements in the data, while sharpening techniques are applied to images [11]. Grayscale images are commonly utilized as input for this process.

Negation: Negation is another technique employed in image processing. It involves creating a negative image where the brightest areas in the original image become the darkest, and vice versa. This method is often utilized in photography.

Subtraction: Image subtraction is a process that entails subtracting the digital pixel values of one image from another. This technique can be helpful in isolating specific features within an image, such as a white tumor from the surrounding areas.

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 [10]

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

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)

B. MODEL COMPILATION:

 # Compile the model with the Legacy optimizer
model_03. compile(loss='categorical_crossentropy', optimizer=sgd, metrics=['accuracy'])
[8]

C. MODEL TRAINING:

history_03 = model_03.fit (train_generator, steps_per_epoch=10, epochs =10, callbacks=[es, cp,Irr], validation data=valid gene

D. TRAINED MODEL SUMMARY:

Layer (type)	Output Shape	Param #
input_4 (InputLayer)	(None, 249, 249, 3)	0
block1_conv1 (Conv2D)	(None, 249, 249, 64)	1792
block1_conv2 (Conv2D)	(None, 249, 249, 64)	36928
block1_pool (MaxPooling2D)	(None, 124, 124, 64)	0
block2_conv1 (Conv2D)	(None, 124, 124, 128)	73856
block2_conv2 (Conv2D)	(None, 124, 124, 128)	147584
block2_pool (MaxPooling2D)	(None, 62, 62, 128)	0
block3_conv1 (Conv2D)	(None, 62, 62, 256)	295168
block3_conv2 (Conv2D)	(None, 62, 62, 256)	590080
block3_conv3 (Conv2D)	(None, 62, 62, 256)	590080
block3_conv4 (Conv2D)	(None, 62, 62, 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, 4096)	115610112
dropout_2 (Dropout)	(None, 4096)	0
dense_7 (Dense)	(None, 1152)	5302528
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)

E. ACCURACY:

For this study, we utilized a pre-existing VGG19 convolutional neural network (CNN) that had been trained for brain tumor classification. The model was trained on the dataset for a total of 10 epochs, resulting in an accuracy rate of 80%. Although increasing the number of epochs could potentially enhance the accuracy further, it is crucial to assess the performance of the model against other architectures to determine if VGG19 is indeed the best choice for this particular task.

F. PLOT PERFORMANCE:

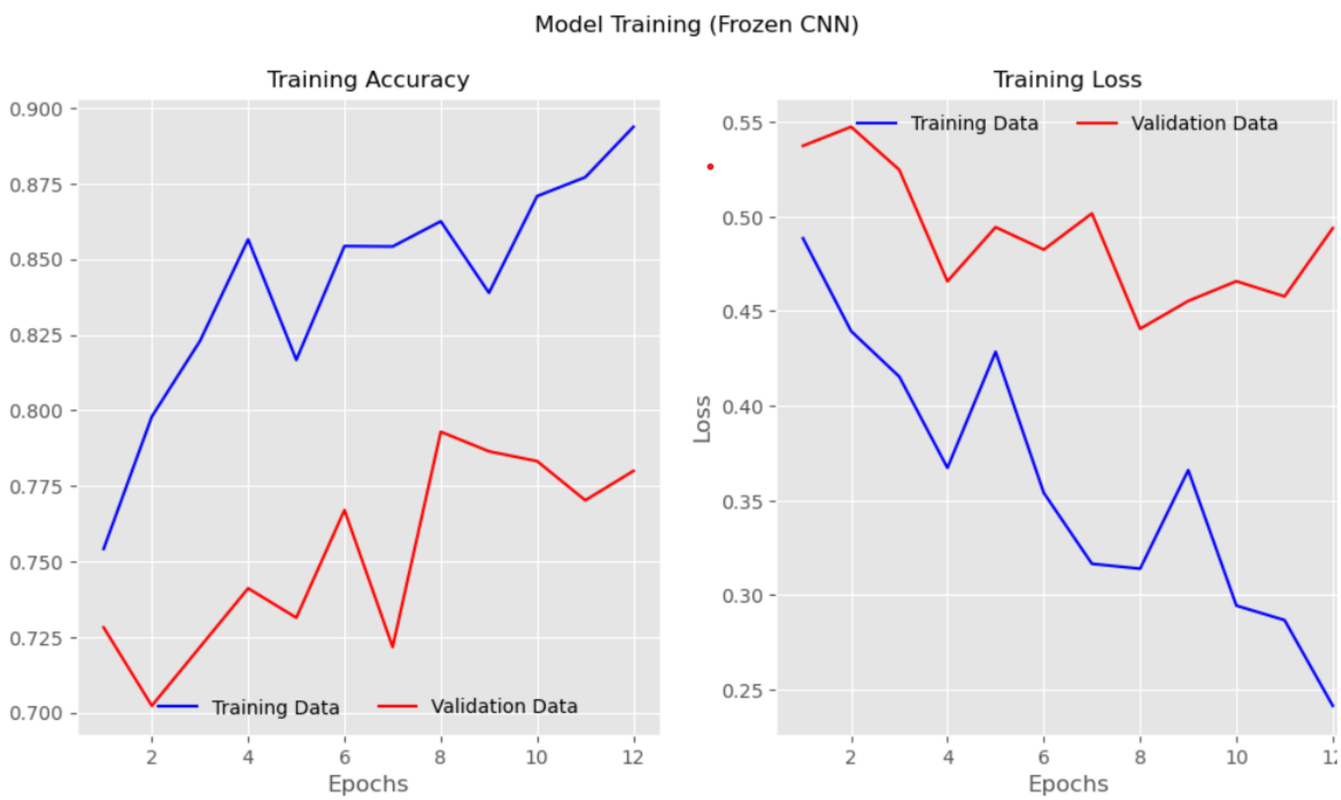

Fig.15: Comparison Graph of the Best Trained Model

V. CONCLUSION

We developed a system for detecting brain tumors using Python and web tech(like flask). This system enables medical professionals to easily upload MRI scans and receive results (identifying the presence or absence of a tumor) through a web interface. Our experiments demonstrated that the system performs admirably in real world scenarios. It effectively distinguishes between tumorous brain scans showing promise as a diagnostic tool for medical practitioners in identifying brain tumors. Various methodologies were explored in constructing this system encompassing image processing well as deep learning approaches. Our investigation revealed that VGG19, a learning model exhibited the accuracy in tumor detection [12]. While there is always room for enhancement in this domain this project has provided me with insights and hands on experience, in developing systems

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