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Deep Neural Network-Based Classification and Detection of Brain Tumors from MRI Images

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***Abstract*: This work introduces a novel technique for detecting brain cancers using magnetic resonance (MR) imaging. Convolutional neural networks (CNNs) are fully utilized in the proposed framework, which employs VGG-16 approaches to enable exact identification of aberrant proliferation of cells in the brain. Preprocessing, segmentation, feature extraction, CNN-based tumor segmentation (or VGG-16), and result detection are the five steps in the proposed solution. The Keras picture dataset from the directory function is loaded and pre-processed, and data augmentation techniques are used to enhance the model's generalizability to additional data. Using the sequential CNN model as a basis, the researchers modify the VGG16 model for brain tumor detection tasks. The accuracy of the model is increased and false positives and negatives are decreased by training and testing the system on a sizable dataset. The suggested method performs better than existing research in the sector, giving physicians and clinicians significant assistance in the automated diagnosis of brain tumor diseases.**

Key Words-MRI, Tumor, CNN, SVM,KNN,VGG16 .

I. INTRODUCTION

The brain is the most important and crucial part in the human body, and One common cause of dysfunction is brain tumors. These tumours are extra cells that develop uncontrollably; brain failure occurs when the body absorbs all nutrients intended for healthy cells and tissues. Currently, doctors use MR imaging to manually determine the location and size of brain tumors. This can lead to faulty detection and is time intensive. Early diagnosis and categorization of brain tumors is critical to avoiding mortality. This paper highlights the development of an automated computer system that recognizes and categorizes cancer blocks in MRI scans from various patients using Convolutional Neural Network (CNN) methods [1]. The system detects brain tumours in cancer patients' MRI scans utilizing image processing techniques such as segmentation, enhancement, and feature extraction. The method consists of four steps: picture preprocessing, segmentation, feature extraction, and classification.

Neural network approach is basically used to increase the performance for detection and classification of Brain tumor through MRI Images. This synergistic strategy uses the characteristics of both disciplines to better discover and categorize brain tumors in medical imaging. According to data from the National Brain Tumour Society, over 4,200 patients in the UK and 1,300 in the United States die each year as a result of primary brain tumours. In 2015, around 29,000 patients in the United States were diagnosed with primary brain tumors, accounting for an estimated 17,760 deaths. In the United States, there are expected to be 24,530 diagnoses of brain tumors in 2021, affecting 13,840 men and 10,690 women [2. Brain tumors are classified as primary or secondary, with primary tumors meaning those that have not metastasized to other parts of the body. Primary brain tumors are classified as benign or malignant; the former develop slowly and have specific limits. Malignant brain tumours, on the other hand, grow quickly and can spread to other sections of the brain. Brain tumors that have progressed to other places of the body and then to the brain are also cause for concern. The World Health Organization established a grading system for brain tumors, identifying approximately 120 varieties. According to studies, gliomas account for over 80% of brain tumors, making them one of the most common forms [3]. Meningioma, epidermoid, medulloblastoma, lymphoma, pituitary adenoma, and glioblastoma are more common types of brain tumors. Prior research on brain cancer detection used deep learning (DL) for segmentation and classification, with a variety of pretrained CNN models such as VGG-16, Dense U-Net, ResNet 50, and AlexNet. [4] [5] have been used for brain tumor segmentation. However, these systems have difficulties in tackling the segmentation difficulty since they rely on invasive and time-consuming manual segmentation of cancer regions.

Furthermore, the small and localised datasets utilized to evaluate and train existing techniques prevent the full representation of all cancer categories. CNN classifiers outperform conventional algorithms because they can

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automatically classify data without operator interaction. A fully automated deep learning model capable of accurately segmenting and categorizing brain tumors is required. To solve the difficulties of imprecise segmentation and ineffective classification, this study proposes a CNN-based methodology. To diagnose brain tumors, a CNN model based on the VGG-16 is trained using transfer learning methods, with the fully connected layer altered, frozen, and replaced. Transfer learning, however, has some restrictions, such as a fixed image input size and a high processing power requirement. [6].

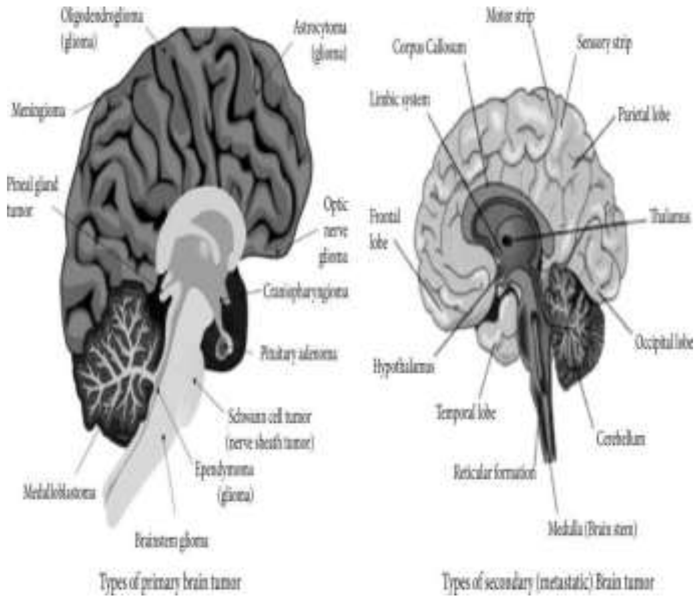

Figure. 1. Different Types of Brain Tumor

The rest of the study is organized as follows: Section 2 examines past study, delving into available models, approaches, and the operation of earlier works in detail. Section 3 includes in-depth information about the proposed framework for brain tumor detection. The proposed approach, which is based on CNN architecture, includes preprocessing, segmentation, postprocessing, and classification steps. It addresses the existing issues related to brain tumors. Section 4 discusses the measuring metrics employed, shows the findings, and reports the experimental outcomes of the proposed methodology. Part 5 discusses and evaluates the proposed approach. Finally, part 6 summarizes the findings and discusses future research directions in this area.

II. LITERATURE REVIEW

DL approaches are currently being used on MR imaging datasets to analyze patient survival rates, locate tumour segments, and sequentially map the structure and texture of brain tumours. There are a variety of CNN architectures that include a brain tumour segmentation and classification system.

Zhou et al. [7] pioneered a unique segmentation approach based on the CNN method. This revolutionary research effectively solved two major issues. To begin, it addressed the constraint of spatial information, which was a common concern in earlier techniques. Second, the model significantly increased multiscale process capabilities, which was previously insufficient. To address the spatial information difficulty, the researchers used the 3D Atrous approach. They also included the pyramid backbone into the framework to effectively handle the second issue with 3D Atrous. The results of this new model were positive, as evidenced by the WT analysis.

Agerwal et al. [8] presented a classification model based on transfer learning. They used a deep learning (DL) model to classify MR pictures into two categories: those with brain malignancies and regular images. For this, the researchers employed a CNN architecture based on the VGG16 model. Their study's findings revealed that the proposed model performed brilliantly, achieving 96.5% accuracy during training and 90% accuracy during testing. Notably, the model demonstrated minimum complexity when evaluated on a
publicly available dataset.

Indra et al. [9] constructed a model that used the T-test for classification and the GLCM (Grey-Level Co-

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occurrence Matrix) for feature extraction. The basic technique entails converting the light information from the brain into a grey matrix and then removing features.

The trial included 40 test results, and the GLCM technique produced both normal and diseased brain images while

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successfully identifying important features. Notably, the study found that every character had a P value less than 0.05, indicating that the extracted attributes were critical for accurately diagnosing brain cancers using the available dataset.

Akil et al. [10] proposed a new CNN-based technique for automatically segmenting glioblastoma brain tumors. They employed a selective attention method to improve the characteristics extracted from MR images. To address the class imbalance issue, the researchers created a spatial imbalance connection that ensures equitable distribution of image patches.

The model's performance was evaluated using the radiologist's dice score, which ranged between 74% and 85%. The results from the BRATS2018 dataset were positive, with median dice scores of 0.90 for WT (Whole Tumour), 0.83 for TC (Tumour Core), and 0.83 for ET.

Bangalore et al. [11] introduced a new deep learning-based algorithm for brain tumor segmentation. To address this, they developed the 3D-Dense U-Net, which successfully handled the binary segmentation issue while avoiding the difficulties associated with multistage segmentation. The suggested technique correctly segmented the WT (Whole Tumour) and CT (Tumour Core) segments of the BRATS2015 dataset, with dice scores of 0.80, 0.92, and 0.84, respectively. Similarly, the dice score on the BRATS2017 dataset was 0.90, with a WT segmentation of 0.80 and a CT segmentation of 0.78. The model performed well on the BRATS2018 dataset, with a dice score of 0.90, WT segmentation of 0.82, and CT segmentation of 0.80 for brain tumor segmentation. Sharif et al. introduced a unique, two-step CNN-based approach for detecting brain tumors [12]. First, the SbDL (Selective Brain Tumor Detection and Localization) model was used to segment brain tumours. A DRLBP (Dynamic Region-based Local Binary Pattern) fusion technique was developed to improve functionality by utilizing the particle swarm optimization (PSO) algorithm. For classification, the Softmax classifier was utilized. The DRLBP technique was developed to improve the classification process, and a phase of contrast improvement was included to allow for image division coordination. The study's outcomes were promising, with the dice score on the BRAST2018 dataset reaching 88.34% for CT (Complete Tumour), 91.2% for WT (Whole Tumour), and 81.84% for ET (Enhancing Tumour). Furthermore, the average accuracy improved.

Naser et al.'s [13] DL-based U-Net technique for detecting brain tumors employs the CNN model. The data was classified using the VGG-16 model. They used the Cancer Imaging Archive (TCIA) dataset, which contained 110 MR images of LGG (Low-Grade Glioma). With a DSE (Dice Similarity Coefficient) of 0.84, the proposed methodology generated excellent results, indicating that the accuracy of brain tumour diagnosis reached 0.92. Furthermore, at the MRI level, their grading models exhibited an accuracy of 0.89, sensitivity of 0.87, and specificity of 0.92. When compared to a publicly available dataset, the grading models' accuracy increased significantly, reaching an amazing 0.95. These data illustrate the efficacy of their DL-based U-Net technique for brain tumor detection and grading.

Khalil et al. [14] introduced the dragonfly algorithm (DA) to segment brain tumors, overcoming the challenge of changing tumor form and size.

The approach involved applying a preprocessing step to 3D-MR images to make it easier to eliminate tumor boundaries. The tumour was then separated from the entire volume of MR images using level set segmentation and a two-step DA clustering approach. The suggested method was evaluated using the publicly accessible BRATS2017 dataset for both training and testing.

III. PROBLEM STATEMENT

Brain tumors are a serious health problem around the world, and getting the right diagnosis quickly is important for effective treatment and better patient survival. Magnetic Resonance Imaging (MRI) is very important for finding brain tumors because it shows brain structures and problems in great detail. However, looking at MRI scans by hand can take a long time, be subjective, and be wrong, which can slow down or change the accuracy of the diagnosis. This study's main goal is to create a strong and effective deep learning-based system that can automatically find and classify brain tumors in MRI images.

The suggested method aims to give doctors consistent, objective analysis to help them make diagnostic decisions faster and more accurately. The VGG-16 model and Convolutional Neural Networks (CNN) will be used to evaluate the complicated patterns in MRI data. If the system can generalize to new, previously unseen data,

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healthcare practitioners will be able to apply the system's accurate tumor identification results in clinical situations. To maintain the highest level of diagnostic precision and accuracy, the system should minimize false positives and negatives.

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a. Existing Solution

Most current methods for detecting brain tumors in MRI data involve a range of machine learning and deep learning approaches. Some of the most well-known contemporary therapies are given here.

Traditional Machine Learning Techniques

Prior to the rise of deep learning, brain tumour detection was based on machine learning techniques such as support vector machines (SVM), k-nearest neighbours (k-NN), and decision trees. These strategies required manually extracting feature information from MRI scans and then classifying the data using machine learning algorithms. These methods were highly successful, but they had substantial limitations, including the need for manual feature extraction and the difficulties finding complicated patterns in MRI scans.

i. ***Convolutional Neural Networks***

CNNs are now at the forefront of image processing tasks like brain tumor detection thanks to the advancement of deep learning. Because CNNs can automatically learn and extract information from MRI images, they are more efficient and accurate than conventional machine learning techniques. Numerous studies have shown that CNNs using a range of architectures, such as AlexNet, VGG, ResNet, and DenseNet, can reliably identify brain cancers [14].

ii. ***Transfer Learning***

Transfer learning is a technique for fine-tuning a previously trained neural network, usually on a huge dataset like ImageNet, for a specific purpose, such as detecting brain tumours. By starting with pre-trained weights, transfer learning can significantly minimize the time and resources required to train a model. Successful transfer learning applications include brain tumour segmentation and identification utilizing models.

iii. ***Multi-Task Learning and Multi-Modal Fusion***

Transfer learning is a way to improve a neural network that has already been trained on a large dataset, like ImageNet, for a specific task, like finding brain tumors. Transfer learning can save a lot of time and money when training a model by starting with weights that have already been trained. Brain tumor segmentation [15] and identification using VGG, ResNet, and Inception models are examples of successful transfer learning applications.

IV. ENSEMBLE METHODS

Ensemble approaches combine the results of multiple models to improve performance. Brain tumour detection systems can improve their accuracy and resilience by merging the output of various CNN architectures or by mixing deep learning and classic machine learning approaches.

The suggested approach makes full use of Convolutional Neural Networks (CNN) and the Visual Geometery Group-16 (VGG16) models to create a precise, accurate, and dependable deep learning-based system for detecting and highlighting brain tumors in MRI data. To accomplish this, the study will first use data augmentation techniques to broaden and diversify the dataset, increasing the model's ability to generalize to new data.

Using Keras' image dataset from directory technique, the dataset will be successfully loaded and pre-processed. The sequential CNN model will serve as the foundation, with the VGG16 model adapted specifically for brain tumor detection tasks. By using a big dataset for training and verification, you can improve the model's accuracy while lowering the risk of false Positives and negatives.

This meticulous training method yielded an accurate and trustworthy model for diagnosing brain tumors. The model will be put to use after being educated with Gradio, which provides medical personnel with an easy-to-use web interface. This user-friendly tool enables customers to upload MRI scans and receive cancer detection findings promptly. The suggested approach intends to improve diagnostic precision, shorten clinical procedures, and ultimately lead to better patient outcomes by providing a dependable and efficient tool for brain tumor detection.

V. CONCEPTS USED

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A. ***Deep Learning***

Deep learning is an area of machine learning that makes use of neural networks. By allowing artificial neural networks to "learn" from a large amount of data, they hope to recreate how the human brain functions. Some of

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the data pre-processing that is frequently necessary for machine learning is reduced by deep learning [16].

B. *Convolutional Neural Network (CNN)*

A CNN is a type of artificial neural network used in deep learning, mostly for image recognition and classification. Consider a CNN model as a mixture of two components: feature extraction and classification. Convolution and pooling are the layers responsible for feature extraction. Following feature extraction, fully connected layers and an activation function work together to produce a classifier [17].

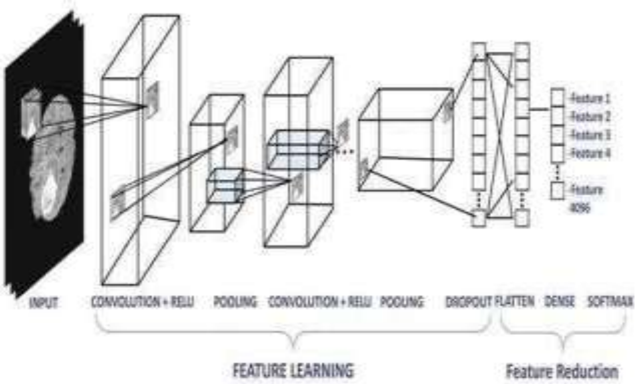

Figure.2. Architecture of Convolution Neural Network (CNN)

A. *Visual Geometry Group-16 (VGG-16)*

The University of Oxford's Visual Geometry Group (VGG) made VGG-16, a convolutional neural network (CNN) architecture, in 2014.A lot of people use CNN architecture to sort images into groups. There are sixteen levels in the VGG-16 architecture. Three of them are totally connected, and the other thirteen are convolutional. A 3x3 kernel with one stride and one padding should be in each convolutional layer. To minimize the size of the feature maps, after every two convolutional layers, max pooling layers with a 2x2 window and stride of 2 are applied. The initial layer has 64 filters, while the final layer has 512. As input proceeds through the layers, the network gains more sophisticated and abstract features. The network's last layer is a SoftMax layer with 1000 outputs, representing the 1000 classes in the ImageNet dataset. Each of the network's fully connected layers includes 4096 neurons. The VGG-16 design is known for its simplicity and consistency. The network is simple to understand, implement, and without affecting the accuracy of system, this enables you to use smaller filters, lowering the parameters number in the network.

B. *Image Preprocessing*

Image preparation often comprises scaling and data augmentation. Image preprocessing can help to speed up model inference and training. At times, the photographs acquired for training may not be the same size or be quite large. In that instance, image processing will assist us in adjusting all of the photographs to the same size as well as minimizing the size of images that are extremely large. This will minimize training time while simultaneously improving performance. The purpose of image pre-processing is to increase specific visual aspects that are necessary for later processing and analysis operations or to reduce undesired noise to enhance the image data.

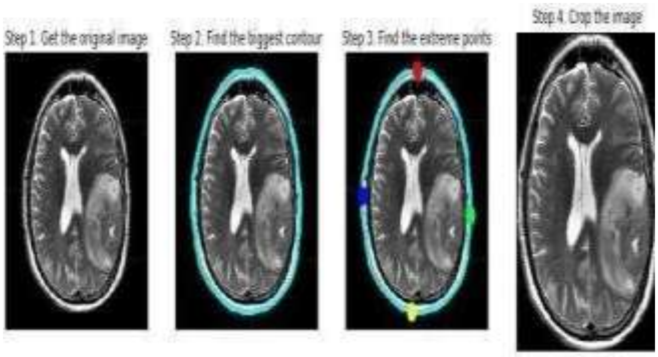

Figure.3. Raw Image to preprocessed image

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C. *Image Augmentation*

Massive amounts of input data are needed for any neural network training. in order to prevent overfitting and allow the model to pick up as many features as feasible. Overfitting is the loss of a neural network's ability to generalize data.

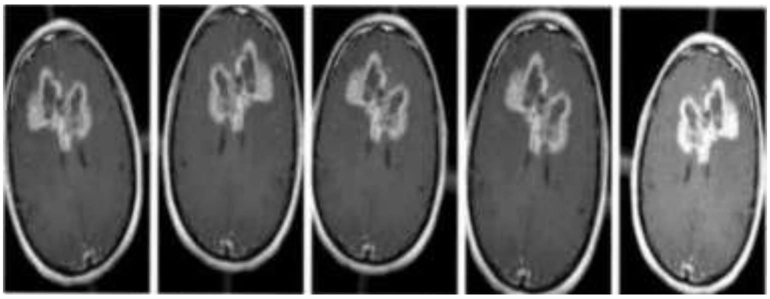

Figure.4. Augmentation process of an MRI Image

However, getting a large amount of data every time is not always achievable [18]. As a result, consider using image augmentation to help expand the data set. Image augmentation often attempts to generate hundreds of images from a single image by changing its size, orientation, and so on. However, image augmentation is only performed during model training and not during model testing.

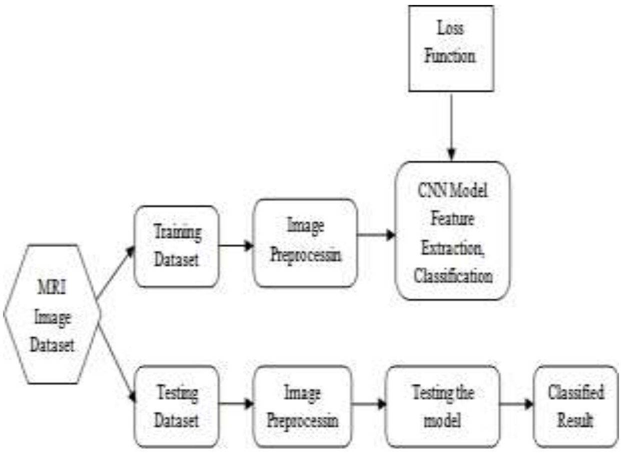

Figure.5. Overall flow of the brain tumour detection system

VI. SYSTEM ARCHITECTURE

Let's now explore how the components of the aforementioned system design function as a whole. To begin with, a dataset is necessary in order to develop any deep learning model. ‘Brain- tumour-Classification’ dataset will be employed for brain tumour identification. The dataset is separated into 4 folders: “no tumour” representing non-tumour photos and remaining three files titled “giloma tumour”,”meningiloma tumour”, pituitary tumour” representing different types of tumours.

The training, testing and validation datasets will now be constructed from the dataset. Here, 30% of BrH35 will be used for testing and validation, and 70% will be used for training. As a result, the testing and training phases of the design are separated. The training phase will begin first. To enhance our dataset and enable the model to extract as many characteristics as practical, it must first preprocess the training dataset using data augmentation. After that, a model will be developed and trained using the preprocessed training dataset and the CNN method. The machine will attempt to learn which properties in this training dataset belong to a tumour. For this approach, the Keras library will be used. By utilizing the loss functions to determine how effectively the neural network models the learned dataset. A loss function compares the target and predicted output values to determine how effectively the neural network matches the training data. During training, make an attempt to decrease this

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difference between the expected and the desirable outcomes. Given that are undertaking a multi classification, a loss function will be implemented. If the loss is low then the model is good to go. Otherwise need to alter the model in such a way that the loss is always less. Now that the training phase is over, the testing phase will begin. To achieve this, reprocess the testing dataset and transmit it to the trained model. The relevant outcomes will be

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shown. For the graphical presentation of the accuracy, loss and other parameters might utilize Python packages.

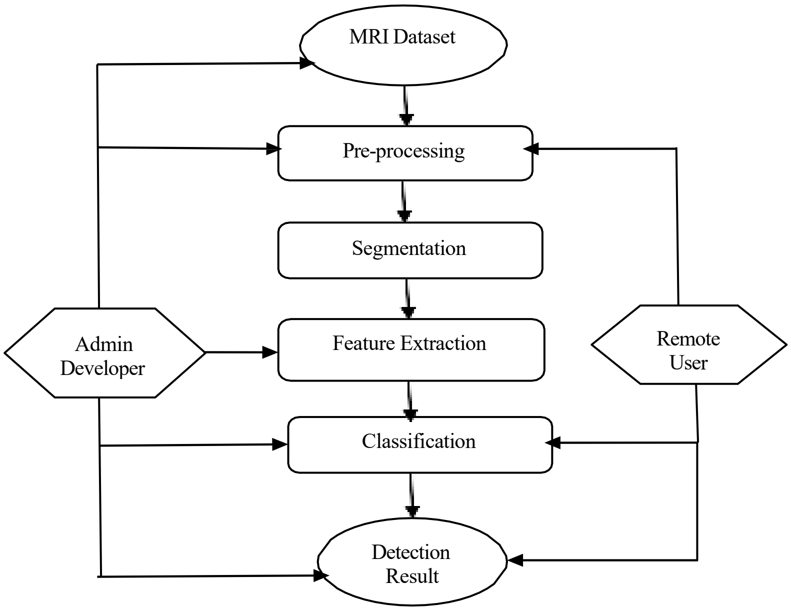

Figure.6. UML Diagram

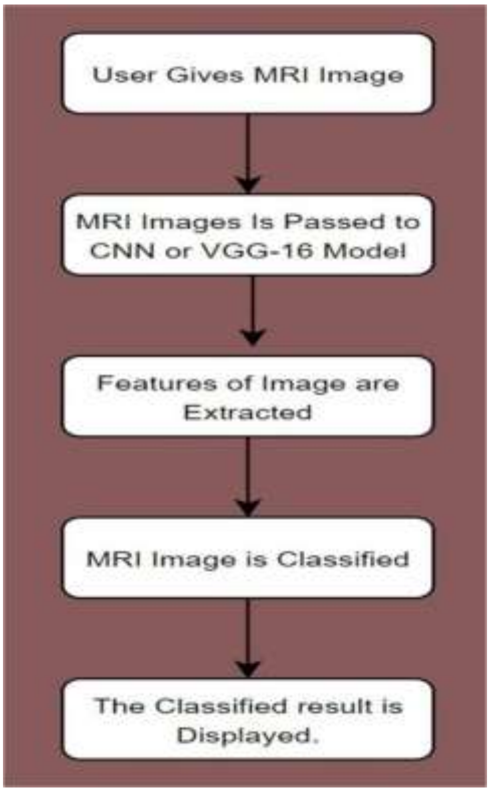

Figure.7. Activity Diagram

The two actors in this use case diagram are the admin and the end user. Six use steps are presented, each of which describes a separate functionality. The administrator gets full access to all functions here. The administrator will first prepare the MRI dataset. Following that, a model trained using the preprocessed dataset and the CNN

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algorithm will be utilized. To determine how successfully the neural networks will imitate the training dataset, the loss function will be applied to the CNN model. The CNN model is now equipped to classify MRI images [19].

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Only the CNN model will be available to the user. In this scenario, the user can input an MRI image, and the model will classify the MRI image. The output will then be shown to the user. The key five actions illustrated in the activity graphic above are:

- Submits an Image (MRI)
- MRI image is transferred to CNN model
- Extraction of Features
- Classification
- Result

A description of each action is provided below:

1. The user will first upload the MRI image.
2. The user-provided MRI image will then be sent to the trained CNN model.
3. The model will now internally extract MRI image features.

Then it will classify the MRI picture based on the features retrieved. Finally, the user will receive Sequence Diagrams describe how processes are carried out through interaction diagrams. They demonstrate how diverse objects interact when working together.

The following are descriptions of the aforementioned sequence diagram.

- The administrator will gather the MRI dataset with labels in order to use it for model training and testing. To preprocess the datasets at this time, training and testing datasets are further divided.
- Data scaling and augmentation are being used. A model will be created using the CNN technique and trained using the training dataset.
- The CNN's ability to model the training dataset is assessed using a loss function.
- After the model is created, its ability to detect cancers is assessed using the testing dataset.
- The classified results.

VII. RESULTS

Table 1. Epoch-based CNN performance of the suggested approach

No of Epochs	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
5	0.4388	80.32	0.5409	71.19
10	0.2890	87.29	0.3629	83.13
15	0.1180	94.53	0.3689	85.29
20	0.0249	98.68	0.3028	89.50
25	0.0120	98.79	0.3139	89.18
30	0.0121	98.89	0.3128	90.50

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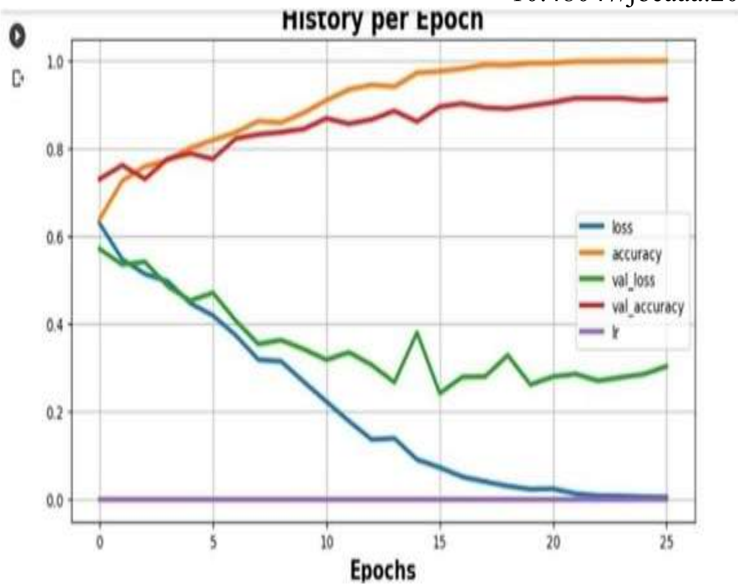

Figure.8. CNN's Epoch History

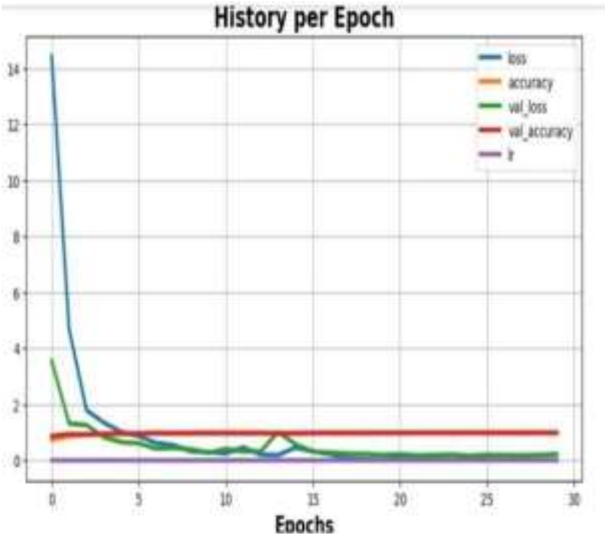

Figure.9. Epoch's History in VGG-16

Figure 8 and 9 gives the idea of how the training loss, training accuracy, validation loss and validation accuracy are going to change for each epoch.

Table 2: The suggested method's performance based on VGG-16 epochs

No of Epochs	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
5	0.7819	94.40	0.5620	94.40
10	0.4269	96.30	0.7559	94.90
15	0.1200	97.59	0.4278	95.79
20	0.0349	98.29	0.289	96.49
25	0.0339	98.48	0.2599	96.29
30	0.0528	98.49	0.2549	96.29

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The performance of the suggested method based on tumor detection throughout five epochs is shown in Table 2. Training loss is 0.7819 and training accuracy is 94.40, validation loss is 0.5620 and validation accuracy is 94.40. Increasing the number of epochs results in a decrease in training loss, an improvement in training accuracy of 98.49, and an improvement in validation accuracy of 96.29 using VGG-16.

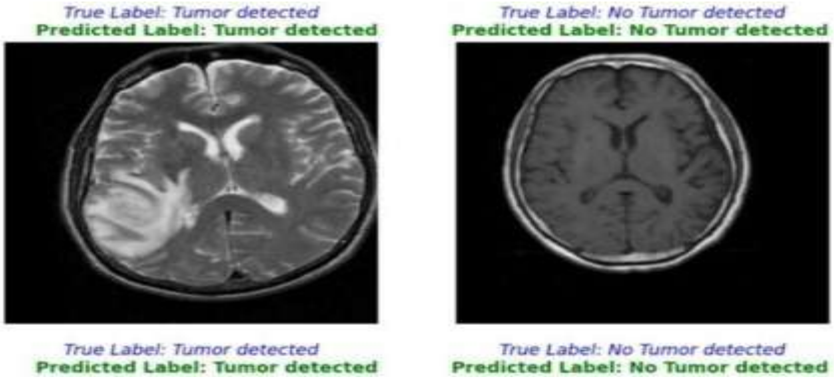

Figure 10. Result for the detection of tumour in VGG-16

VIII. CONCLUSION

In summary, the suggested deep learning-based technique offers a reliable and quick way to identify brain cancers in MRI data. By eliminating the challenges that physicians face while attempting to identify brain tumors, the technology enhances clinical operations, increases diagnostic precision, and ultimately improves patient outcomes. Using the most recent deep learning techniques, such as data preparation, data augmentation, and fine-tuning the VGG16 model, the system achieves very good accuracy and the capacity to generalize. The system's user-friendly interface makes it simple for healthcare professionals to employ the trained model in clinical settings. These kinds of technologies are a big step toward better healthcare, especially when it comes to finding and treating brain tumors. The suggested way to make diagnosing and treating brain tumors better is usually a good one, and it could make a big difference in the lives of patients.

REFERENCES

[1] M. R. Gupta, V. Rajagopalan, and B. V. V. S. N. P. Rao, "Glioma grade classification using wavelet transform-local binary pattern based statistical texture features and geometric measures extracted from MRI," Journal of Experimental Theoretical Artificial Intelligence, vol. 31, no. 1, pp. 57–76, 2019.

[2] D. N. Louis, A. Perry, G. Reifenberger et al., "The 2016 World Health Organization classification of tumours of the central nervous system: a summary," Acta Neuropathologica, vol. 131, no. 6, pp. 803–820, 2016.

[3] R. L. Siegel, K. D. Miller, and A. Jemal, "Cancer statistics, 2015," CA:a Cancer Journal for Clinicians, vol. 65, no. 1, pp. 5–29, 2015.

[4] R. L. Siegel, K. D. Miller, and A. Jemal, "Cancer statistics, 2019," CA: a Cancer Journal for Clinicians, vol. 69, no. 1, pp. 7–34, 2019.

[5] R. L. Siegel, K. D. Miller, H. E. Fuchs, and A. Jemal, "Cancer statistics, 2021," CA: a Cancer Journal for Clinicians, vol. 71, no. 1, pp. 7–33, 2021.

[6] Z. H. Zhou, Z. He, and Y. Jia, "AFPNet: a 3D fully Convolutional neural network with atrous-convolution feature pyramid for brain tumor segmentation via MRI images," Neurocomputing, vol. 402, pp. 235– 244, 2020

[7] K. Agerwal, N. Sharma, M. Kumar, and J. Nirvikar, "Brain tumor classification using CNN," Advances and Applications in Mathematical Sciences, vol. 20, no. 3, pp. 397–407, 2021

[8] Z. J. Indra and Y. Jusman, "Performance of GLCM algorithm for extracting features to differentiate normal and abnormal brain images," IOP Conference Series: Materials Science and Engineering, vol. 1082, no. 1, article 012011, 202

[9] M. Akil, R. Saouli, and R. Kachouri, "Fully automatic brain tumor segmentation with deep learning-based selective attention using overlapping patches and multi-class weighted cross entropy," Medical Image Analysis, vol. 63, article 101692, 2020

[10] C. G. B. Yogananda, B. R. Shah, M. Vejdani-Jahromi et al., "A fully automated deep learning network for brain tumor segmentation," Tomography, vol. 6, no. 2, pp. 186–193, 2020

[11] M. I. Sharif, J. P. Li, M. A. Khan, and M. A. Saleem, "Active deep neural network features selection for segmentation and recognition of brain tumors using MRI images," Pattern Recognition Letters, vol. 129, pp. 181–189, 2020

[12] M. D. Naser and M. J. Deen, "Brain tumor segmentation and grading of lower-grade glioma using deep learning in MRI images," Computers in Biology Medicine, vol. 121, article 103758, 2020

[13] H. A. Khalil, S. Darwish, Y. M. Ibrahim, and O. F. Hassan, "3D-MRI brain tumor detection model using modified version of level set segmentation based on dragonfly algorithm," Symmetry, vol. 12, no. 8, p. 1256, 2020

[14] J. S. Fu, K. Singhrao, X. S. Qi, Y. Yang, D. Ruan, and J. H. Lewis, "Three-dimensional multipath DenseNet for improving automatic segmentation of glioblastoma on pre-operative multimodal MR images," Medical Physics, vol. 48, no. 6, pp. 2859–2866, 2021

10.48047/jocaaa.2024.33.07.53

[15] J. Z. Zhang, J. Zeng, P. Qin, and L. Zhao, "Brain tumor segmentation of multi-modality MR images via triple intersecting U-Nets," Neurocomputing, vol. 421, pp. 195–209, 2021.