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Brain Tumor Classification using Pre-Trained Deep Convolutional Neural Networks

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***Abstract*:** The classification of brain diseases is an extremely challenging task owing to their intricate and sensitive nature. Brain tumors are significant and life-threatening, requiring accurate and prompt diagnosis for effective treatment planning. MRI is a crucial medical imaging tool, providing detailed, non-invasive brain imaging. MRI is crucial in brain tumor detection, influencing the diagnosis and management of these conditions. The approach initiates with dataset preprocessing, encompassing MRI scans and clinical data from individuals with various brain conditions, both tumor and non-tumor cases. Dataset is categorized as training and testing sets. Identifying tumors in MRI scans encompasses various stages, including image preprocessing, feature extraction, and classification. The system uses Convolutional Neural Networks with VGG-16 and Xception models for brain image classification. VGG-16, known for its deep architecture and strong feature extraction, is used alongside Xception, a highly efficient model for image classification. The results indicate significant advantages of Xception's transfer learning models over VGG-16. Transfer learning models automatically extract hierarchical features from raw image data, eliminating the need for manual feature engineering. The feature extraction capability empowers CNNs to capture nuanced and complex patterns in brain images, elevating their diagnostic accuracy. The dataset combines figshare, SARTAJ, and Br35H sources, comprising 7,023 MRI images of human brain is divided into four classes: meningioma, no tumor, pituitary and glioma. This study results affirmed the method's effectiveness, achieving an impressive 94% accuracy in brain tumor detection. Users can input brain MRI images to predict tumor types and receive detailed diagnosis information based on accuracy of the model. Experiment results show that the proposed system surpasses existing systems in disease prediction efficiency.
Keywords: *Brain tumor classification, medical imaging, convolutional neural network, transfer learning, deep learning.*

1. Introduction

The most crucial organs in the human body, the brain aids in decision-making and regulates the operation of all other organs. It is principally in charge of managing the daily voluntary and involuntary bodily functions and acts as the control center for the nervous system. The brain tumor is an unregulated, rapidly growing mass of undesirable tissue inside our brain that takes on the appearance of a fibrous web. Approximately 3,540 children below the age of 15 receive a diagnosis of brain tumors annually. A comprehensive understanding of the brain tumors and the various stages they progress through are essential to both the prevention and also the effective management of the condition.

An abnormal mass of tissue marked by unregulated proliferation and multiplication of the cells, seemingly unregulated by mechanisms governing normal cells, is termed an intracranial tumor or brain tumor. While there are over 150 recognized categories of tumors on the brain, the primary categories are primary and metastatic type of brain tumors. Tumors originating in the brain from tissues of brain or the structures around it. Primary tumors can be classified as either malignant or benign. The tumors which originating in different areas of the body, like the lungs or breast, and later metastasizing to brain, usually through the circulatory system, are referred to as metastatic of brain tumors. Metastatic tumor is malignant and classified as cancerous. The types of tumors are shown in Fig 1.

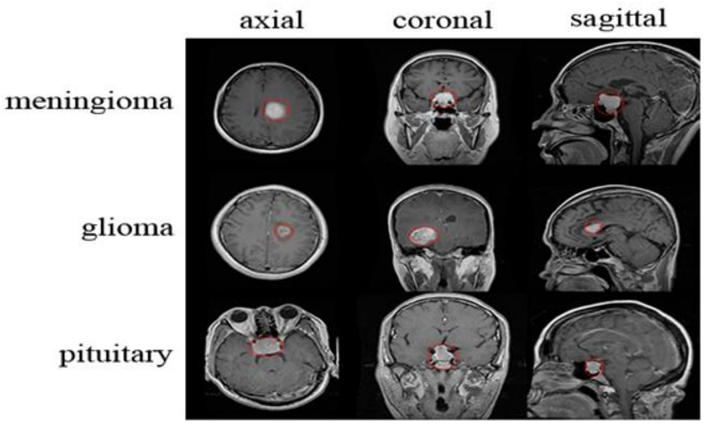

Fig. 1. Brain Tumor Types

2. Related work

Saeed Mohsen et al.[1] described using hyper-parameter optimization to deploy VGG19 models and Res-Next101_32 × 8d to improve the precision of brain tumor classification and detection. These two models have the advantage of simplicity in architecture, potentially reducing computational costs (training time), and they are built upon a transfer learning process. Kaggle repository contained a dataset that was used for testing and training the models. The first of six steps involved uploading the dataset of MRI images, which had been divided into images for training and testing. Image normalization, or pre-processing the MRI scans, was the second step. Determining the overall training epochs was the third step. The fourth stage involved using a fitting function to train the model with the chosen MRI images. The fifth stage involved assessing the predictive capability with MRI test images of VGG19 model, and concluding stage was to assess the performance of the model using various criterion on MRI test pictures.

In clinical field, precise imaging is essential to producing accurate diagnoses as demonstrated by Solanki, Shubhangi, et al. [2]. The methods employed to capture artifacts, including CT, PET, and magnetic resonance imaging, influence the efficacy of the clinical images. Real images from a magnetic resonance scan may include a great deal of unnecessary and undesired detail. A consequence of Rician noise is magnetic resonance imaging. This survey encompasses all the noteworthy characteristics and the latest research conducted so far, along with its limitations and challenges. Enhancing comprehension of how to conduct new research effectively and efficiently within a reasonable timeframe will benefit researchers. A generic approach is still needed, despite the significant contributions made by deep learning approaches. When training and testing are performed using comparable achievement features, such as intensity range and resolution, these methodologies yield superior results; additionally, even the smallest deviation between the training and testing images directly impact the robustness of the methodologies. Subsequent research endeavours could be undertaken to identify brain cancers more accurately, using real patient data as opposed to mediocre methods of capturing images (scanners). Classification accuracy may be improved by combining deep features with handcrafted characteristics.

Shah, et al.,[3] carried out to diagnose brain tumors, VS-BEAM, an innovative an algorithm for computer-aided diagnosis has been implemented. To ascertain whether the malignant growth is present in MRI images, the ensemble architecture combines several models. The final abnormality is determined by the algorithm through a voting mechanism, which increases diagnosis accuracy and efficiency. To enhance feature extraction efficiency, SE attention modules are integrated into CNN architecture. We came to the conclusion that SE modules of attention paired with CNN is more rational than standalone CNN networks. The algorithm of VS-BEAM mainly made to utilizes the ensemble learning with different classifier algorithms. In contrast, second approach also functioning as a dense classifier, handles the multiclass classification of brain tumor as three binary class classification problems. Meanwhile, the first method employs a traditional dense network to address the issue as classification of multiclass. Lastly, a Bayesian classifier that estimates the posterior distribution is used by the third classifier to categorize the tumor. During the evaluation stage, the suggested approach for identifying and dividing the MRI pictures of brain tumor meets efficient performance standards. The comprehensive model showcased promising outcomes and could be implemented in continuing clinical investigations for computer-assisted diagnosis of brain tumors.

Ferdous et al. [4] introduced a framework based on teacher-student architecture, LCDEiT designed to classify the tumor in MRIs of brain. The framework consists of an additional attention-based image transformer which is backbone for image classification, along with a teacher model is based on the gated CNN pooling for knowledge extraction. Necessity for an extensive dataset for vision transformers has been mitigated by the insights acquired from the teacher model. Introducing an additional attention to backbone of the transformer model, which reduces the intricacy linearly concerning number of the patches, effectively eliminates quadratic intricacy stemming from self-attention within the transformer encoder. Based on the results, the student model based on transformers, central to suggested framework, achieves optimal classification outcomes, with F1-scores (0.978 and 0.937) to the BraTS-21 and Figshare datasets. The underscores their effectiveness that employing image transformers with strong learners in realm of the diagnostic imaging, particularly in situations to which rapid computation is significant for initiating the treatment in significant medical conditions. To tackle the difficulties associated with a higher misclassification rate for classes with smaller samples, future applications may consider employing methods for handling imbalanced datasets, like class-wise augmentation. Despite the improved performance of the suggested LCDEiT model on two distinct datasets from Figshare and BraTS-21, enhancing the model's universality could be achieved by broadening the scope of the experimental database.

Two research issues, including the security issue with the IoMT environment and the classification of brain tumors, were resolved by Ramprasad et al. [5][6][7]. The objective of research is to offer a comprehensive result to address the issues. This study concentrates for securing brain tumor images by incorporating TIWT into the MIW implementation. This is aimed at ensuring confidentiality and privacy of patient information when the medical data is transmitted over internet of medical devices. The objective is to secure the transmission of source image of the tumor within protected environment, preventing unauthorized access to the image. Another objective of the study is to evolve a precise system for classifying brain tumors. It employs transfer learning techniques, specifically BWO-GA for feature extraction and for segmentation a transfer learning-based RU-Net model is used. Subsequently, AlexNet, a transfer learning network, used for classifying segmented tumor region into malignant and benign tumors[8][9][10]. The primary aim is to enhance the accuracy of tumor classification, allowing timely prediction and possibility of saving lives. The process of segmentation at the IoMT- receiver employs RU-Net model which precisely identifies the tumor location. Additionally, the BWO-GA is employed to remove the multilevel features, and optimal features are selected based on attributes found in the nature. Furthermore, an AlexNet that is based on transfer learning is trained with the best features for tumor classification[11].

3. Existing Methodologies

Utilize machine learning algorithms within the existing system for the brain tumor classification, employing algorithms to the feature extraction and classification. In the field of brain tumor detection from medical images, the machine learning algorithms plays a significant in enabling timely diagnosis and successful treatments of these disorders[12][13][14].

Despite being relatively simple, the K-Nearest Neighbours (K-NN) algorithm remains a valuable method. It aids in identifying similar cases within a dataset by allocating class label to data points based on their majority class of their closest neighbours in feature space. AdaBoost and Gradient Boosting exemplify ensemble methods that have demonstrated effectiveness in boosting classification accuracy through the integration of predictions from multiple classifiers[15][16]. These methods leverage the strengths of diverse base classifiers to enhance the model's generalization and robustness. When it comes for the brain tumor detection, these machine learning algorithms are a great resource for medical professionals. They help identify brain tumors quickly and accurately, which improves patient outcomes[17][18].

Another useful tool is Support Vector Machines (SVM), particularly for binary classification tasks like identifying tumor and non-tumor regions in medical images. To create precise classifications, SVMs can make use of a variety of features that have been extracted from the images, such as texture, intensity, and shape descriptors[19][20]. Decision trees and random forests are also frequently used. They can be applied to classification tasks and have

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the advantage of feature selection. These algorithms help distinguish between regions that are tumorous and those that are not, using features and attributes extracted from medical images[21].

4. Proposed methodologies

To determine whether the brain contains tumors or other abnormal growths, detection of tumors over the brain is a significant medical procedure. Prompt identification of brain tumor is needed for the favourable patient outcomes and successful treatment. The process that is most frequently used makes use of medical imaging techniques, specifically CT and MRI scans. Trained radiologists and physicians can see and locate tumors thanks to these non-invasive techniques that produce detailed images of the brain. In order to help radiologists interpret medical images, machine learning and artificial intelligence—including deep learning models like CNNs have witnessed a growing utilization. By automatically identifying and categorizing tumors from photos, these models increase accuracy and efficiency. Accurately detecting the brain tumor is essential for formulating adequate treatment plans, which may encompass chemotherapy, radiation therapy, surgery, or a blend of these approaches. Timely diagnosis and detection are made imperative to enhance outcomes of the patient and also the quality of life.

"Brain Tumor Detection Using Transfer Learning," the proposed system, its given name, seeks to significantly enhances the accuracy and efficiency of detection of brain tumor in medical imaging. Using pre-trained deep learning models on extensive datas and refining them for specific task of brain tumor detection is how this system harnesses the capabilities of transfer learning. Collecting and preprocessing data are pivotal stages in the system architecture. An array of MRI scan images, both with and without tumors, is collected. Preprocessing methods encompass data augmentation, pixel normalization, and image resizing, enhancing the quality and variety within the dataset. The focal point of the system is the transfer learning approach. In this context, the core architecture involves the pre-trained deep learning model as VGG16 or Inception. Brain tumor detection task leverages features and knowledge extracted from a large dataset in other domains. The convolutional layers of that pre-trained model extract features, while fully connected layers adjust their model to complexities of classification of brain tumor. This quickens their development process and enhances the model's efficacious brain tumor detection capabilities. The system excels in its capacity to attain high accuracy with a significant reduction in the need for a large dataset dedicated to brain tumor images.

The dataset is divided into three separate subsets in order to thoroughly assess the system's efficacy and capacity for generalization: training, validation, and testing. The robustness of the model can also be verified and the chance of overfitting reduced by using cross-validation techniques. Another crucial component of fine-tuning is hyperparameter tuning, which entails optimizing variables like learning rates, batch sizes, and the use of regularization strategies. This fine-tuning procedure is essential to guaranteeing optimal performance and an effective convergence of the model. Next step involves the model evaluation, in which the recall, F1-score precision, and accuracy among other established metrics are employed to assess the performance of the system's. This assessment is carried out on the specific testing dataset, which enables a precise comprehension of the capacity of system's to precisely detect brain tumors. Additionally, this system can expedite the development of brain tumour detection models and make them accessible for real-world medical applications, ultimately improving patient care and outcomes. Fig 2 illustrates the proposed model.

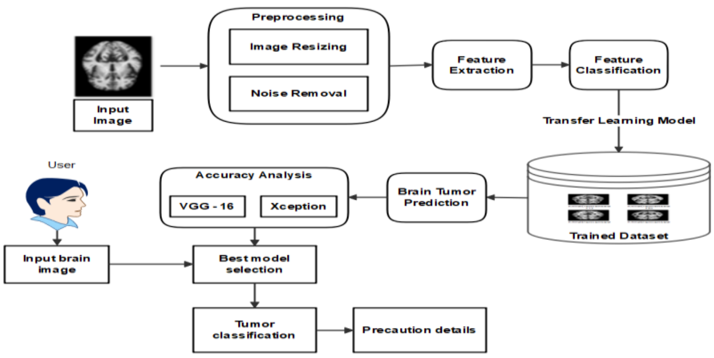


Fig. 2. Proposed Model Diagram

Fig 2, images are collected from KAGGLE websites related to brain tumor images like Pituitary tumor, No tumor, Meningioma tumor and Glioma tumor. And then perform preprocessing steps such as noise removal using median filtering algorithm. Finally select the pretrained model such as VGG16 model and Xception CNN model. Based on tumor classification, calculate the performance system in terms of accuracy and confusion matrix. In testing phase, input the brain image and perform classification using best model file. Finally predict the tumors and provide the precaution details

4.1 VGG16 MODEL

The VGG16 model is a CNN that has become renowned for its efficacy in tasks of computer vision, especially in classification of image. Developed at the University of Oxford by the Visual Geometry Group (VGG), it participated in ImageNet Large Scale Visual Recognition Challenge (2014). The "16" there in its name refers to the number of weight layers it has.

Key characteristics and components of the VGG16 model include:

- Convolutional Layers: VGG16 comprises 13 convolutional layers designed for feature extraction from input images. Subsequently, these layers are succeeded by max-pooling layers that downsample the feature maps to capture hierarchical information.
- Fully-Connected Layers: VGG16 includes three fully connected layers, succeeded by an output layer for classification. These fully connected layers are tasked with making conclusive decisions regarding the input image's class.
- Receptive Fields: VGG16 uses relatively small 3x3 convolutional in their layers. The architecture results in very small receptive fields for each neuron, enabling it to grasp intricate details within the images.
- Stacking Convolutional Layers: The distinctive feature of the VGG16 architecture is its repeated stacking of convolutional and pooling layers, facilitating the learning of features at various scales.
- ImageNet Pretraining: VGG16 underwent pretraining on the ImageNet dataset, encompassing millions of labelled images spanning thousands of categories. This pretraining provides the model with a broad understanding of various visual concepts.
- Transfer Learning: VGG16's pretraining makes it an excellent choice for transfer learning. You can fine-tune the model on a specific task, like brain tumor detection, by replacing the last few layers while keeping the pretrained layers' weights intact.
- Deep Network: VGG16 is relatively deep compared to its predecessors and is capable of learning intricate features and patterns from images. However, this depth also results in increased computational complexity.

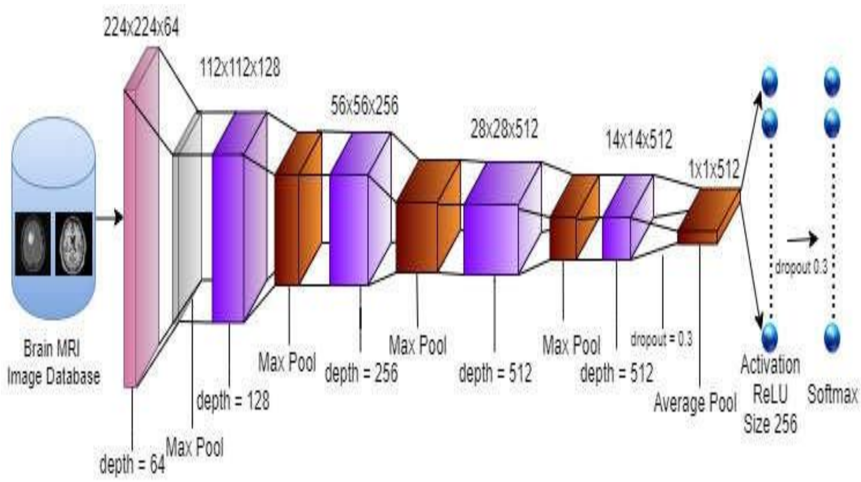


Fig. 3. VGG16 model

4.2 XCEPTION CNN MODEL

Xception, pronounced as "exception", is the Convolutional Neural Network (CNN) tailored specifically for classification of image tasks in deep learning. Introduced in 2017 by François Chollet, Xception, a component of

Keras library, now seamlessly integrated with TensorFlow. Xception, an abbreviation for "Extreme Inception," improves upon the Inception architecture, optimizing it for both efficiency and accuracy. Here are a few notable features of the Xception model:

- The Depthwise Separable Convolutions: The fundamental innovation in the Xception architecture lies in the application of depthwise separable convolutions. This entails splitting the conventional convolution operation into two parts such as the depthwise convolution and the pointwise convolution. Depthwise convolution applying a single filter to every input channel and the pointwise convolution consolidates the results through the application of 1x1 convolutions. This division markedly diminishes the parameter count, enhancing the efficiency of model.
- Efficient Performance: Utilization of the depthwise separable convolutions enables Xception to attain exceptional efficiency, lowering the computational burden while preserving accuracy. This is particularly valuable for applications with limited computational resources, such as mobile devices.
- Increased Depth: Xception features a significantly deeper architecture compared to Inception models. This depth enables it to capture intricate and hierarchical features from images, rendering it suitable for a diverse array of computer vision tasks.
- Fully Convolutional: Xception is fully convolutional, meaning it can process inputs of varying sizes. This adaptability makes it well-suited for the tasks like object detection and segmentation of image, where the input dimensions can vary.
- Transfer Learning Capability: Like other pre-trained models, Xception supports transfer learning. The model can be fine-tuned for a specific task, leveraging its pre-trained weights on extensive datasets like ImageNet.

Fig. 4. XCEPTION CNN Model

5. Experiment Outcomes

In this analysis, we input datasets of BRAIN MRI images gathered from sources like figshare, SARTAJ, and Br35H, analyzing three classes: Pituitary tumor, Glioma tumor, no tumor and Meningioma tumor. Table 1 provides details about the datasets.

Table 1: Image collection

Image class	Total no of the images
Tumor of Glioma	1321
Tumor of Meningioma	1339
Tumor of Pituitary	1457
Images of No tumor type	1595

To evaluate the system's efficiency, different metrics such as accuracy, sensitivity, specificity, precision and error rate is calculated.

Number of the true favourable outcomes - the optimal favourable outcomes prediction.

False Positives - FP represents count of the incorrectly anticipated positive results.

Number of the true unfavourable outcomes- accurate prediction of a negative results.

False Negative - FN refers to the count of correct negative predictions subtracted from the actual number of negatives.

Accuracy

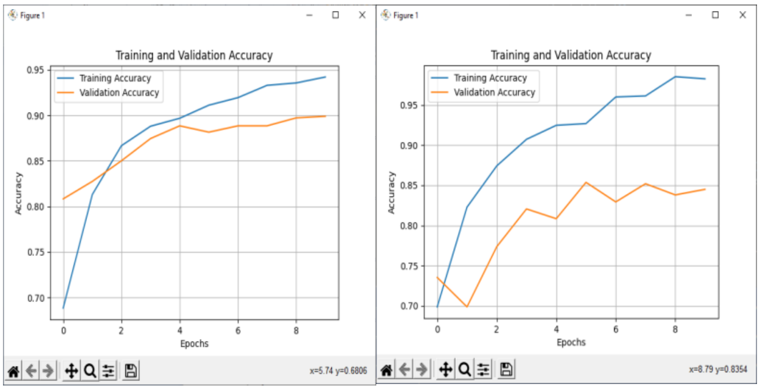
Accuracy (ACC) refers to the proportion of entirely correct predictions to the entire test dataset and it is expressed as 1 - ERR. Accuracy value ranges from lower end (0.0) to higher end (1.0).

$$ACC = \frac{TP+TN}{TP+TN+FN+FP} \text{ x } 100$$

Table 2: Accuracy table

ALGORITHM	ACCURACY
VGG 16	90
Xception CNN	84

As per the depicted graph, the accuracy rate of the proposed CNN algorithm surpasses that of the current approach. The Fig 5 illustrates the training accuracy for the VGG16 and Xception CNN models.



a) VGG 16 model **b) Xception CNN model**

Fig. 5. Training accuracy

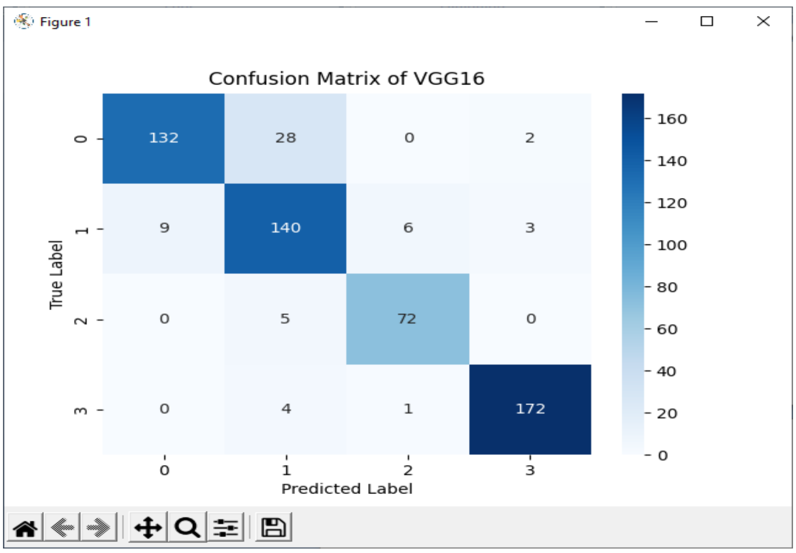


Fig. 6. The Confusion Matrix of VGG16 Model

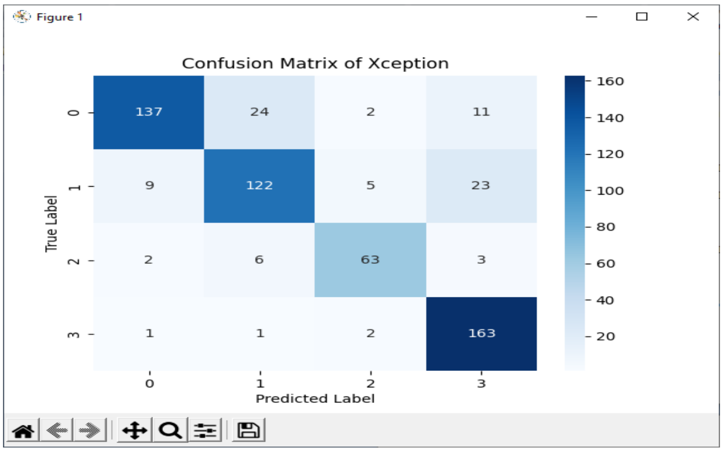


Fig. 7. The Confusion Matrix of Xception CNN

From above mentioned figures the VGG16 model provides high level accuracy in disease prediction

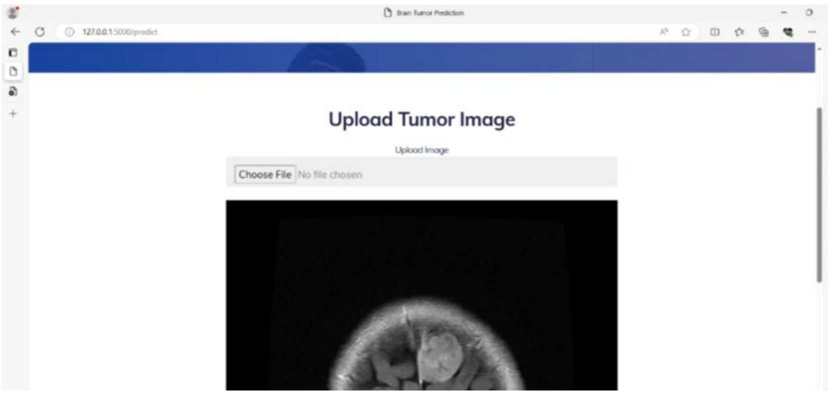


Fig. 8. Disease prediction

Fig. 9. Precaution details

6. Conclusion

In conclusion, the utilization of the VGG16 and Xception models for the identification of brain tumors marks a substantial progress in the realm of medical imaging and healthcare These highly effective deep learning models, recognized for their proficiency in image analysis, provide valuable tools to aid healthcare professionals in the prompt and accurate diagnosis of tumors over the brain. VGG16, with its well-established architecture and strong image classification capabilities, provides a solid foundation for this critical task. Its adaptability and versatility make it a reliable choice for classifying brain MRI and CT scans, enhancing efficiency and precision of the brain tumor identification. VGG16 model is customizable and fine-tuned to accommodate specific dataset requirements, allowing for precise brain tumor detection while adhering to ethical and regulatory guidelines in healthcare. On the other hand, the Xception model, characterized by its computational efficiency and feature extraction prowess, demonstrates exceptional potential for brain tumor analysis. The depthwise separable convolutions within the Xception architecture reduce computational costs, making it a suitable choice for resource-constrained environments. Its versatility encompasses a range of medical imaging tasks, including identifying abnormalities in X-rays and MRI scans. From the model implementation, VGG16 model provided improved efficiency in disease prediction. So user can input the image and classified brain tumor types with diagnosis details

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