# CLASSIFICATION OF BRAIN TUMOR USING CONVOLUTIONAL NEURAL NETWORKS

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## Abstract

The human brain is a crucial organ composed of billions of cells. When cells in the brain undergo abnormal and uncontrolled division, it can result in the formation of tumors, which can exert immense pressure on nerves and blood vessels, potentially causing irreversible harm to the body. An extensively employed method to identify brain tumors is Magnetic Resonance Imaging (MRI). The term IoMT represents the Internet of Medical Things, which refers to the combination of networked technology with medical devices and applications for remote monitoring and management of patient health. Advanced machine learning algorithms and image segmentation techniques can classify these tumors. This study utilized a Convolutional Neural Network framework, specifically ResNet-50, for classification of brain tumors into three categories: meningioma, glioma and pituitary tumor. By incorporating ResNet-50, the study was able to tackle the problem of vanishing gradient and facilitate training of deeper neural networks. The MRI image dataset is preprocessed and augmented to improve image quality. The CNN ResNet-50 framework ensures effective super-resolution of brain images, improving tumor classification accuracy, especially for early cancer nodules. Performance is evaluated based on training and testing accuracy.

*Keywords*—Brain Tumor, CNN Architecture, ResNet-50, Deep Learning, Classification.

## I. INTRODUCTION

An abnormal cluster or mass of cells in the brain or nearby tissues is referred to as a brain tumor. Brain tumor can be classified as either non-cancerous (benign) or cancerous (malignant). They can originate from various types of brain cells like neurons, glial cells, and meninges. The causes of brain tumors are not fully comprehended, but certain risk factors such as exposure to radiation, family history, and genetic syndromes have been identified. Symptoms of brain tumors differ based on the tumor's location and size but generally

include headaches, seizures, vision or hearing problems, mood or personality changes, and difficulties with coordination or movement. Diagnosis typically involves imaging tests such as MRI or CT scans along with a biopsy to verify the tumor type and grade. Treatment options depend on the patient's age, health, and the tumor's type and location. Prompt identification and managing them in a timely manner are essential for improving the likelihood of a favorable result.

Gliomas originate from glial cells in the brain and can be either benign or malignant, accounting for approximately 30% of all brain tumors. Meningiomas arise from the meninges, the protective tissue layers covering the brain and spinal cord. They are often benign and grow slowly, but can occasionally be malignant, accounting for about 15-20% of all brain tumors and being more prevalent in women than men. Although they can appear at any age, meningiomas are most common in adults aged 50 and above. Pituitary tumors form in the pituitary gland situated at the brain's base, which produces hormones controlling various bodily functions like growth and reproduction. These tumors are usually non-cancerous and grow slowly, accounting for about 10-15% of all brain tumors. While many pituitary tumors are small and symptom-free, larger ones can cause various symptoms dependent on their size and position.

The field of brain tumor detection and diagnosis has seen significant advancements with the implementation of deep learning. Artificial Neural Networks are utilized in Deep Learning, a Machine Learning technique, to classify and learn from data. Medical imaging has widely adopted this approach to detect and diagnose various illnesses, including brain tumors. One of the primary advantages of deep learning in brain tumor detection is its capacity to rapidly and precisely analyze vast amounts of medical imaging data. This can facilitate accurate diagnosis and treatment decisions by doctors and radiologists. Moreover, deep learning algorithms can detect even slight changes in brain imaging, which might be overlooked by human observers. Another benefit of deep learning in brain tumor detection is its capability to learn and adapt as more data is fed into the algorithm. This can enhance the accuracy and efficacy of the algorithm in detecting brain tumors. Overall, deep learning has the potential to diagnose and detect brain tumors, with improved accuracy, quicker diagnosis, and better patient outcomes.

## II. LITERATURE SURVEY

Shaila Shanjida et al., A CNN-KNN model was employed to detect and classify brain tumors[1]. The CNN was responsible for extracting features, while two classifiers, SoftMax and KNN, were employed by the researchers to automatically identify and classify different brain tumor types. The KNN classifier demonstrated superior performance compared to the SoftMax classifier in classifying various brain tumors. The CNN-KNN approach yielded a high accuracy of 95.7%.

Muhammad Ali et al., The CNN framework was utilized for classification, while tumor segmentation was accomplished using the Particle Swarm Optimization (PSO) technique [2]. Classification was performed using the CNN framework, while tumor segmentation was achieved by utilizing the Particle Swarm Optimization (PSO) technique. The suggested approach achieved segmentation results of 98.11% and classification results of 98.25% for Dice similarity coefficient (DSC), with accuracies of 98.9%

Ardhendu Sekhar, et al utilized a transfer learning based classification model for the classification of brain tumor [3]. Data pre-processing is minimal for the proposed model. The suggested model exhibits the greatest classification accuracy

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for the 3-class tumour classification issue when compared to other modern algorithms. The experimental findings show that the suggested technique outperforms both existing methods using CNN and current standard ML methods for the dataset.

Shaveta Arora et al., devised a method that combines data feature mapping with MRI images [4]. The Gray-Level Co-occurrence Matrix texture-based selection approach was employed to select features, which is a commonly used method. Various models were used to categorize brain tumors. The performance of the classifiers like SVM and random forest was assessed using several transfer learning models, including VGG16 and Inception V3.

Seifedine Kadry et al. conducted research on analyzing brain tumor using brain MRI samples using techniques such as VGG16 and VGG19 [5]. After feature extraction, the SoftMax and SVM classifiers were used for multi-class categorization, and the performance of each method was evaluated based on the total accuracy achieved. The study revealed that the VGG19 with SVM-Cubic achieved the highest overall accuracy (96%) compared to other methods.

## III. PROPOSED METHODOLOGY

In this paper, the proposed methodology for brain tumor classification is based on the Convolutional Neural Network (CNN) model. The ResNet-50 architecture of CNN is used. A pre-trained ResNet model can be employed to extract various features from an image. The ResNet architecture is constructed with convolutional layers, batch normalization layers, and residual blocks. The initial layers of the model are responsible for extracting features, such as edges and corners, whereas the deeper layers of the model extract more complex features, such as object parts and shapes. After extracting these features, a softmax activation function to execute the task of classification

into the relevant classes – Glioma, Meningioma and Pituitary tumor. Fig.1 illustrates the workflow of the proposed methodology.
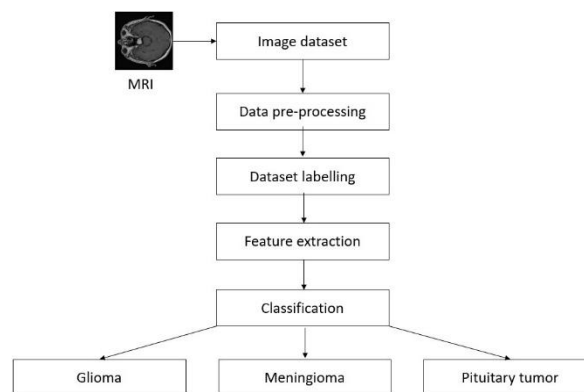
Fig. 1. The workflow of proposed methodology

### A. *Image dataset:*

In this study, 3064 T1-weighted, contrast-enhanced MRI imaging datasets of brain tumors from 233 individuals will be used to conduct experiments. The collection includes samples from three different forms of brain tumors, meningioma (comprising 708 samples), glioma (comprising 1426 samples), and pituitary tumor (comprising 930 samples). Fig.2 represents the MRI dataset featuring various kinds of brain tumors.
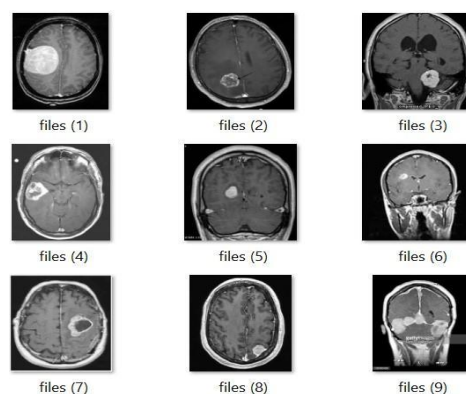
Fig. 2. The MRI dataset featuring various kinds of brain tumors.

## B. *Image pre-processing:*

The objective of the preprocessing stage is to improve the quality of MR images depicting brain tumors and make them suitable for subsequent processing by imaging modalities or clinical professionals. It further aids in optimizing the parameters of MR images. Preprocessing can eliminate undesirable distortions and enhance certain characteristics that are crucial for the specific application being utilized. These characteristics may be adjusted as per the application's requirements. Proper preprocessing of images is necessary for the software to operate correctly and generate the intended outcomes.

The subsequent steps describe the data preprocessing procedure:

Step 1: Conversion of the data format into image format

To create a dataset of images for training a Python library model, first, the MATLAB array file can be opened using the h5py Python library. Then, the images can be saved in JPEG format using the matplotlib library. For reading images in DICOM format, the pydicom library can be implemented. Following that, image arrays can be processed using the NumPy library, and JPEG image files can be stored using the OpenCV library. This will make it easier to create a dataset of images that can be tested and validated.

Step 2: Increase Image Channels

Utilize the OpenCV library to open the image and convert it from one channel (i.e. grayscale) to three channels (i.e. RGB channels).

Step 3: Crop and Resize Images

Use the OpenCV library to resize the image to 512 x 512 and crop it as necessary to produce a standardized resolution. This step is necessary in deep learning since all the images should have the same resolution.

Step 4: Image Augmentation

Image augmentation involves modifying an existing image by applying changes such as rotation, cropping, zooming, flipping, etc., and including the altered version in the training dataset for the neural network. To create a custom dataset class, image augmentation is used to augment each image at various angles (0,5, 90, 120, 180, 270, 300, 330 degrees). Implementing image augmentation enables real-time loading, augmentation, and training of data, rather than caching all training samples in memory for augmentation. After image augmentation, the number of samples are increased from 3064 to 24512 samples which are split during model training. Fig.3 represents the dataset after image augmentation.
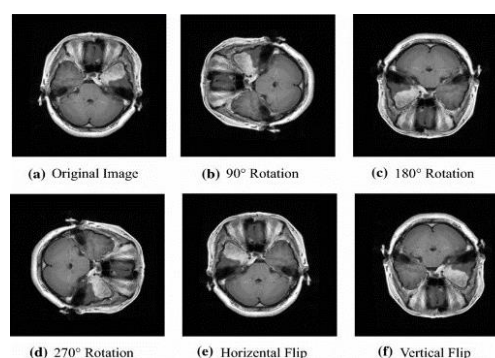


Fig. 3. Image augmentation applied on a given dataset

## C. *Dataset labeling:*

Dataset labeling is a crucial machine learning process that involves assigning descriptive and informative labels to raw data to provide context. Pickle, a useful Python tool, facilitates sharing, committing, and reloading of pretrained machine learning models. It is used to serialize and deserialize Python object structures. Pickling is a technique in Python programming language that converts Python objects, such as lists, dictionaries, or class instances, into a byte stream or character stream. This process is also called serialization. The pickled object

can be stored in a file or transmitted over a network, and later unpickled to recreate the original object in memory. Pickling is commonly used for data storage, data transmission, and for sharing data between different Python programs or different machines.

### D. CNN- ResNet 50 architecture:

CNN-ResNet50 refers to a Convolutional Neural Network (CNN) that is based on the ResNet50 architecture. ResNet50 is a deep learning model that contains 50 layers. It is specifically designed to eliminate the vanishing gradients problem in deep neural networks, which can affect the training of the model. The name "ResNet" stands for "Residual Network," which refers to the use of skip connections or residual connections between layers.

ResNet is a type of neural network architecture that was specifically designed for very deep networks, i.e., those with dozens or even hundreds of layers, which were previously challenging to train due to the vanishing gradient problem. Vanishing gradient is a problem which occurs during the training of deep neural networks, particularly those with many layers. The problem arises when the differential value of the loss function with respect to the parameters in the previous layers of the network become very small as they are backpropagated from the output layer to the input layer during training. This can cause the early layers to learn very slowly or not at all, leading to poor performance of the network. Several techniques have been developed to mitigate the vanishing gradient problem, including the use of alternative activation functions, normalization techniques, and more effective weight initialization methods. The ResNet architecture introduces a novel approach called "residual learning," which enables the network to skip over certain layers and directly learn the underlying

mapping between inputs and outputs. This is accomplished by introducing shortcut connections, or "skip connections," that allow the network to bypass one or more layers and propagate the input directly to a deeper layer in the network.
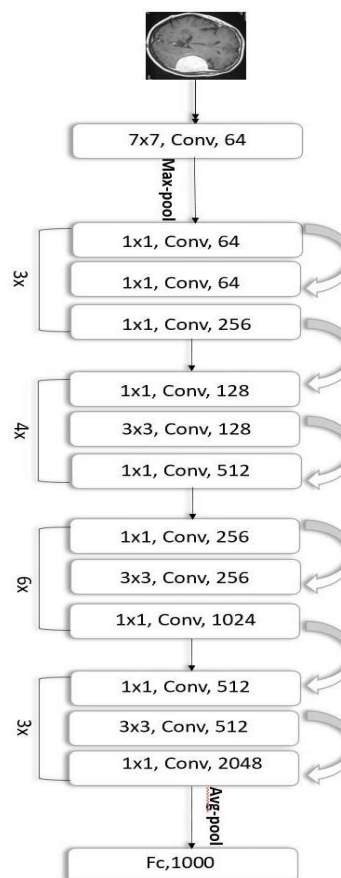


Fig. 4. Architecture of ResNet-50

In a ResNet, each building block or layer is comprised of several convolutional layers followed by a batch norm layer and a ReLU function which is a non-linear activation function. The skip connections are then added to the output of the last convolutional layer before the activation function. Fig.4 represents the skip connection in ResNet. The use of skip connections in ResNets allows for much deeper networks to be trained without suffering from the vanishing gradients problem. Fig.4. represents the architecture of ResNet-50.

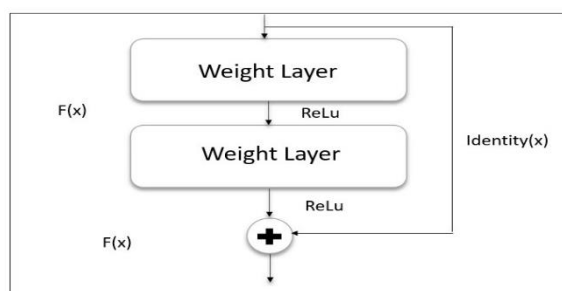*Eur. Chem. Bull.* **2023**,*12(Special Issue 5), 1770-1779*

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Fig. 5. Skip connection in ResNet

The ResNet-50 architecture comprises various components, as listed below:

1. A 2-stride 7x7 kernel convolutional layer with 64 kernels.
2. A max pooling layer with a 2-stride.
3. 9 more layers with 64 kernels using 3x3 convolutions, 64 kernels using 1x1 convolutions, and 256 kernels using 1x1 convolutions. These 3 layers are repeated 3 times.
4. 12 more layers with 128 kernels using 1x1 convolutions, 128 kernels using 3x3 convolutions, and 512 kernels using 1x1 convolutions, repeated 4 times.
5. 18 more layers with 256 kernels using 1x1 convolutions, 256 kernels using 3x3 convolutions, and 1024 kernels using 1x1 convolutions, repeated 6 times.
6. 9 more layers with 512 kernels using 1x1 convolutions, 512 kernels using 3x3 convolutions, and 2048 kernels using 1x1 convolutions, repeated 3 times.
7. An average pooling layer followed by a fully connected layer.

## IV RESULT ANALYSIS

### A. Model Training and Testing:

To train the model, the dataset was divided using a cross-validation approach. The dataset consisted of 3064 samples, with 70% allocated for training, 15% for validation, and 15% for testing to evaluate model accuracy. The training set has 2144 images, the validation set has 460 images, and the test set has 460 images, making a total of 3064 images.

The number of augmented training samples are 17152, the number of augmented validation samples are 3680 and the number of augmented testing samples are 3680. After the model is trained, the performance of the model is tested on the testing set to acquire a final assessment of the model's accuracy.

TABLE I. Type and number of samples of Brain tumor images before and after augmentation

| Type of tumor | MRI samples before augmentation | MRI samples after augmentation |
|---|---|---|
| Meningioma | 708 | 5664 |
| Glioma | 1426 | 1136 |
| Pituitary tumor | 930 | 7440 |
| Total | 3064 | 24512 |

### B. Confusion Matrix:

A commonly utilized tool for assessing the effectiveness of a machine learning model is a confusion matrix. It illustrates how many of the proposed system's predictions were correct and incorrect when compared to the actual results. The matrix is often shown as a square table with the predicted categories in the columns and the actual target categories in the rows. The number of accurate predictions for each class is indicated in the table's diagonal cells, whereas erroneous classifications are indicated in the off-diagonal cells. The parameters are represented in Table.II. Several performance metrics can be computed using a confusion matrix to determine the model's advantages and disadvantages. Fig.6 shows the confusion matrix obtained.
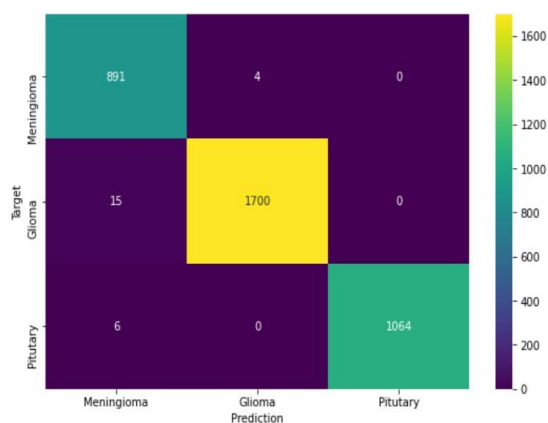
Fig.6. Confusion matrix

TABLE II. Confusion matrix parameters

| Type of tumor | True positive | True negative | False positive | False negative |
|---|---|---|---|---|
| Meningioma | 891 | 2764 | 21 | 4 |
| Glioma | 1700 | 1961 | 4 | 15 |
| Pituitary | 1064 | 2610 | 0 | 6 |

## C. *Evaluation Parameters:*

The quantitative analysis involves the utilization of the following evaluation metrics: Accuracy is the ratio of the correct predictions and the total number of predictions. Recall is defined as the number of true positives divided by the total number of actual positives. Precision is defined as the number of true positives divided by the number of predicted positives. The F1 score can be found by taking the harmonic mean of precision and recall. Omission Error represents the proportion of instances that were actually positive but were wrongly predicted as negative or neutral, whereas Commission Error refers to the proportion of instances that were predicted as positive but were actually negative or neutral.

$$PRECISION = \frac{TP}{TP+FP} \qquad (1)$$

$$RECALL = \frac{TP}{TP+FN} \qquad (2)$$

$$ACCURACY = \frac{TP+TN}{TP+TN+FP+FN} \qquad (3)$$

$$OMISSION\ ERROR = \frac{FN}{FN+TP} \qquad (4)$$

$$COMMISSION\ ERROR = \frac{FP}{FP+TP} \qquad (5)$$

$$F1\ SCORE = \frac{2*(PRECISION*RECALL)}{(PRECISION+RECALL)} \qquad (6)$$

where,

True Positive (TP): a scenario where the model accurately predicts a positive outcome and the outcome is truly positive.

False Positive (FP): a scenario where the model incorrectly predicts as positive when it is actually negative.

True Negative (TN): a scenario where the model accurately predicts a negative outcome while the outcome is truly negative.

False Negative (FN): a scenario where the model mispredicts as negative but is actually positive.

TABLE III. Evaluation Parameters

| Types of tumour | Meningioma | Glioma | Pituitary |
|---|---|---|---|
| Accuracy | 0.993 | 0.994 | 0.998 |
| Precision | 0.976 | 0.997 | 1.000 |
| Recall | 0.995 | 0.991 | 0.994 |
| F1-Score | 0.985 | 0.993 | 0.996 |
| Omission Error | 0.0044 | 0.0087 | 0.0056 |

| Commission Error | 0.0230 | 0.0023 | 0 |
|---|---|---|---|

The loss metrics graph and accuracy metrics graph are plotted as represented in Fig.7. From the figures it is inferred that as the number of epochs are increased, the loss tends to reach a minimum value and the accuracy is maximized.
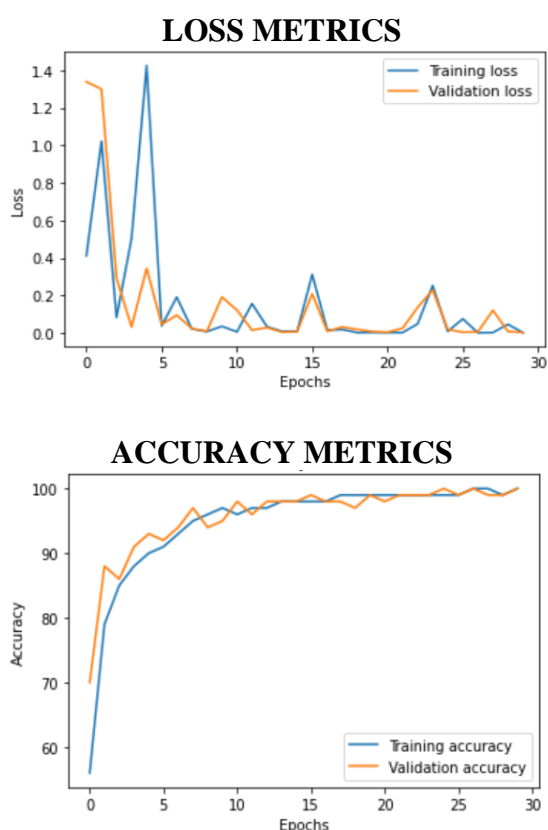


Fig. 7. Training performance

The proposed model has been trained and the performance of the model has been evaluated. The validation accuracy is found to be 98.88% and test accuracy of 99.32% The precision, recall, F1-score, commission error and omission error are found for Meningioma, Glioma and Pituitary tumor respectively as mentioned in Table III.

### D. Comparison with existing methods:

The proposed CNN ResNet-50 model is compared with several existing methodologies for classification of brain tumor. Table IV represents the comparison of the proposed model with existing methodologies.

TABLE IV. Comparison of the proposed model with existing methodologies

| Reference | Year | Methodology | Accuracy in % |
|---|---|---|---|
| Sultan B. Fayyadh et al.,[6] | 2020 | CNN | 98.029 |
| Seifedine Kadry et al., [5] | 2021 | VGG19-SVM | 96 |
| Hareem Kibriya et al.,[4] | 2021 | GoogLeNet-SVM | 98 |
| Muhammad Ali et al., [2] | 2022 | CNN-PSO | 98.9 |
| Shaila Shanjida et al., [1] | 2022 | CNN-KNN | 95.7 |
| Proposed methodology | 2023 | ResNet-50 | 99.32 |

### E. Web Interface:

A web-based interface has been developed which enables users to access the application from any device without the need to install any software. This makes the application more accessible and user-friendly, as users can access it from anywhere, anytime. The trainable parameters of the model are saved in .pt format using the built-in functionality of Torch Vision. The stored weights are then updated by another Python file that downloads the Torch Vision framework. This framework is utilized to classify brain tumors in images stored in databases. A web page was created to provide users with the ability to upload MR images and classify tumors by selecting different
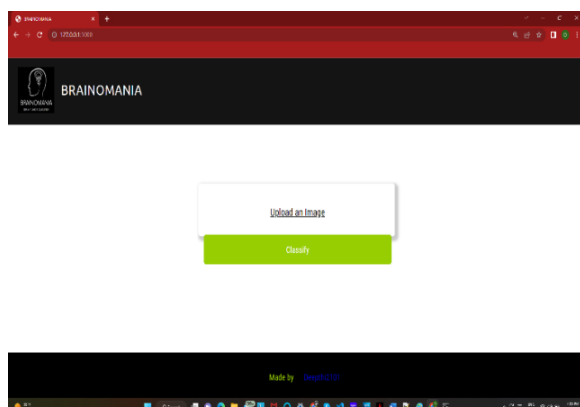
options, enabling real-time access to the model.



Fig. 8. A screenshot of the homepage

After selecting the "Upload Image" button, a checkbox will appear which permits the choice of an MRI image. The web application has the ability to categorize images according to their tumor types. Fig.8 and Fig.9 shows the screenshots of the home page and the classifier page.
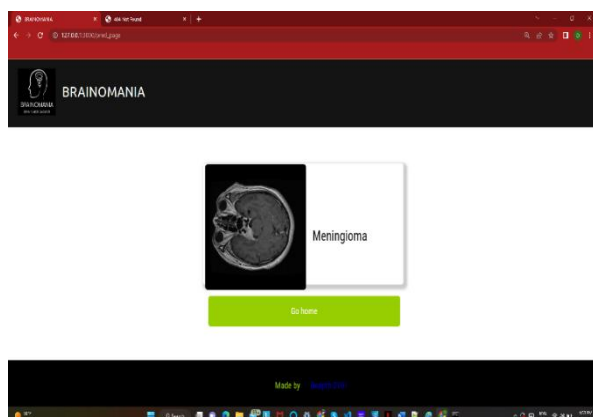


Fig. 9. A screenshot of the test image being classified correctly as Meningioma

## V. CONCLUSION

IoMT stands for the Internet of Medical Things, which refers to the integration of medical devices and applications with networked technology, allowing for the remote monitoring and management of patient health. A CAD system, or computer-aided diagnosis system, is a software tool that assists healthcare professionals in the analysis of medical images. The primary objective of this study is to classify brain tumors into three types: meningiomas, gliomas, and pituitary tumors. To achieve this, the paper proposes a method using deep learning techniques. The method involves preprocessing and enhancing MRI images, and then matching them with a fine-tuned Convolutional Neural Network (CNN) model, specifically ResNet-50, for tumor classification. The proposed model achieved the highest classification accuracy with minimal computational effort, with an accuracy of approximately 99.32%. The validation accuracy was excellent, and the loss was minimal. Consequently, this study can be a useful tool in the medical field for easily identifying different types of brain tumors. In conclusion, the development of a brain tumor classifier is a critical task in the medical field for diagnosis and treatment. With the use of advanced machine learning techniques and imaging technologies, it is now possible to develop accurate and efficient classifiers that can detect brain tumors with high precision. The development of such a classifier can help doctors and medical professionals to identify the location and type of the tumor, which could guide treatment decisions and improve patient survival rates. However, it is important to note that the development of a brain tumor classifier requires extensive research, data collection, and testing to ensure its accuracy and effectiveness. Therefore, continued research and collaboration between medical professionals and machine learning experts are crucial to further advance the field and improve patient care.

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