



# International Journal of Multidisciplinary Research in Science, Engineering and Technology

*(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)*



**Impact Factor: 8.206**

**Volume 9, Issue 4, April 2026**



## International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

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# Hybrid Deep Learning Framework for Brain Tumor Detection using CAE and CNN

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**ABSTRACT:** Accurate and early detection of brain tumors through MRI imaging is critical for effective clinical diagnosis and treatment. This paper introduces a hybrid deep learning framework that integrates Convolutional AutoEncoders (CAE) (for robust, unsupervised feature extraction with Convolutional Neural Networks (CNNs)—notably VGG16 and VGG19—for high-performance classification. The CAE compresses complex MRI data into essential representations, which are subsequently analyzed by CNN models to perform both binary and multi-class classification tasks.

The system is designed for multi-attribute prediction, extending beyond tumor detection to include patient age group (adult/child), gender (male/female). The model was developed and evaluated using a Kaggle brain MRI dataset, which includes annotated MRI images along with patient metadata such as age, gender, and tumor type. Preprocessing steps such as normalization, resizing, and augmentation were applied to improve model generalization and robustness. The proposed CAE+CNN hybrid model demonstrated consistently strong performance across various evaluation metrics including accuracy, precision, recall, and F1-score. It represents a significant advancement in the application of deep learning to medical image analysis and patient profiling.

**KEYWORDS:** Brain tumor detection, deep learning, Convolutional AutoEncoder (CAE), Convolutional Neural Network (CNN), VGG16, VGG19.

## I. INTRODUCTION

Brain Tumor detection using MRI imaging is essential for accurate diagnosis and effective treatment planning. Traditional methods rely on manual analysis of medical images, which is time-consuming and prone to human error. With the advancement of deep learning, automated approaches have significantly improved the accuracy of medical image analysis. AutoEncoders (AEs) enable unsupervised feature extraction and efficient data compression, capturing important patterns from complex MRI data. Convolutional Neural Networks (CNNs), particularly architectures like VGG19, are highly effective for image classification tasks due to their ability to learn hierarchical features. However, limited availability of medical datasets poses challenges, which can be addressed using transfer learning techniques. In this work, a hybrid deep learning framework combining Convolutional AutoEncoders (CAE) and CNN is proposed. The CAE extracts meaningful latent features, which are then classified using a fine-tuned CNN model. The system leverages MRI data for accurate brain Tumor detection and classification. Experimental results demonstrate improved performance in terms of accuracy and reliability. This approach provides an efficient and automated solution for brain Tumor diagnosis and supports clinical decision-making.

## II. LITERATURE REVIEW

Brain Tumor detection using medical imaging has gained significant attention with the advancement of deep learning techniques. Earlier approaches mainly relied on traditional machine learning methods, where features were manually extracted from MRI images. However, these methods were limited in their ability to capture complex patterns, leading to lower accuracy. With the emergence of Convolutional Neural Networks (CNNs) and Convolutional AutoEncoders (CAE), researchers began to achieve better performance in medical image classification.



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Author& Year	Method Used	Dataset	Performance
Driss Lamrani (2022)	CNN	Kaggle dataset of Brain MRI Images	~96.33% Accuracy
D Agalya (2024)	CAE+CNN(VGG19)	Kaggle dataset of Brain MRI Images	Accuracy ~92.8%
D. Agalya (2025)	CAE + LTSM	BRATS Dataset	~96.2% Accuracy
Shubhangi Solanki (2023)	SVM	DICOM dataset	Accuracy ~ 98%
R. Rajasree et al. (2018)	U-Net, CNN	BRATS 2015	Accuracy ~ 96.36%

### III .PROBLEM STATEMENT

Even though medical technology has improved a lot, detecting Brain Tumor accurately is still not easy. Doctors need to go through many MRI scan images, which increases their workload and can sometimes lead to mistakes. In some places, there are not enough specialists, which causes delays in diagnosis. Existing systems also have some drawbacks, such as limited data and lower accuracy in real-world conditions. Because of these issues, there is a need for a better system that can provide accurate results and help in early detection.

### IV. OBJECTIVES

The main goal of this project is to create a system that can automatically detect Brain Tumor using deep learning. The objectives are:

- To prepare MRI scan images for model training
- To improve data quality using augmentation techniques
- To use models like CAE, CNN(VGG16 and VGG19)
- To apply Deep learning for better results
- To classify images into normal and Tumor categories
- To evaluate the model performance
- To build a simple interface for user interaction

### V. FLOWCHART

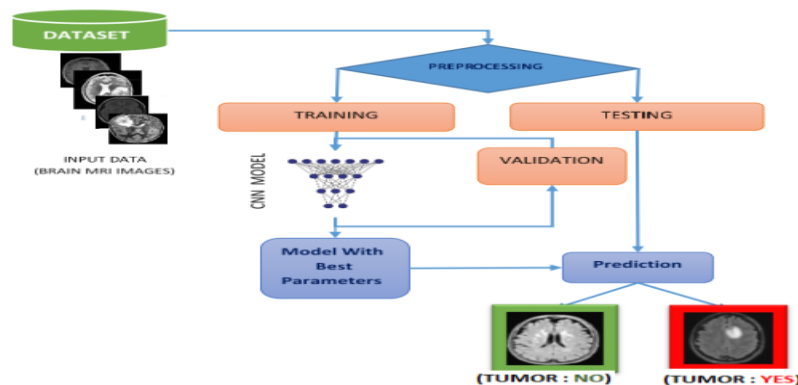


Fig 1 Flow Chart



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The proposed system begins with collecting a Brain MRI image dataset, which forms the foundation for training and evaluation. The dataset is divided into training and testing sets to ensure proper model validation. In the training phase, the images undergo preprocessing steps such as noise removal, normalization, and enhancement to improve quality. To handle class imbalance, the Convolutional AutoEncoder(CAE) technique is applied, which generates synthetic samples for underrepresented classes. All images are resized to 224×224 pixels to maintain uniform input dimensions for the CNN model. The processed data is then used to train the convolutional neural network, allowing it to learn important features from the images.

In parallel, the test dataset is used to evaluate the trained model. After training and testing, the model performs classification to determine whether the MRI image is with Tumor or not. And further extends to classify Multi-class Attributes (Patient's age, Gender) for better treatment.

### VI. METHODOLOGY

#### Overview

The proposed system follows a structured approach to detect and classify Brain Tumor from MRI images using deep learning techniques. The process includes data collection, preprocessing, model training, evaluation, and deployment through a web interface.

#### Step 1: Data Collection

The first step is to collect MRI images of Brain from available datasets. The dataset contains both normal and Tumor images, including patient's age and gender. This data is used to train and test the models.

#### Step 2: Data Preprocessing using CAE

Before giving the images to the model, preprocessing is performed to improve data quality. This includes:

- Resizing images to a fixed size
- Normalizing pixel values
- Labeling images into categories

These steps help the model learn more effectively.

#### Step 3: Data Augmentation using CAE

To increase the amount of training data and avoid overfitting, augmentation techniques are applied. Some common methods used:

- Rotation
- Flipping
- Zooming

This makes the model more robust and improves performance.

#### Step 4: Model Development

In this project, three deep learning models are used:

- CNN (VGG16 and VGG19)

Deep learning is applied to VGG16 and VGG19 using pre-trained weights, which helps in achieving better accuracy in less time.

#### Step 5: Model Training

The models are trained using the prepared dataset.

- The training process uses an optimizer
- Loss function is used to measure error
- The model learns patterns from MRI images

Training is done for multiple epochs until the model performs well.

#### Step 6: Model Evaluation

After training, the models are evaluated using standard metrics:



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- Accuracy
- Precision
- Recall
- F1-score

These metrics help in comparing different models and selecting the best one.

### Step 7: Model Selection

Based on the evaluation results, the best-performing model is selected. In this project, CAE+CNN (VGG16) provides better accuracy compared to CAE+CNN(VGG19), so it is chosen for deployment

### Step 8: Deployment with Web Interface

The final model is integrated into a web application.

- Backend is developed using Streamlit
- Frontend is created using HTML, CSS, and JavaScript

Users can upload MRI images through the interface, and the system will display the prediction result (Tumor or No Tumor)

## VII. IMPLEMENTATION OF THE SYSTEM REQUIREMENTS FOR HARDWARE AND SOFTWARE

### Hardware Requirements

The system requires a standard computing device with sufficient processing capability for training and testing deep learning models. A system with at least an Intel i7 processor (or equivalent), 16 GB RAM, and optional GPU support is recommended for faster computation. Adequate storage is also required to handle medical image datasets.

### Software Requirements

The implementation is carried out using Python programming language along with deep learning and data processing libraries such as TensorFlow, Keras, NumPy, and OpenCV. Development is performed using environments like Google Colab. A web framework such as Streamlit is used for building the user interface, and standard tools like HTML, CSS, and JavaScript are used for frontend development.

## VIII. DEEP LEARNING MODELS

### 1. Convolutional AutoEncoders (CAE)

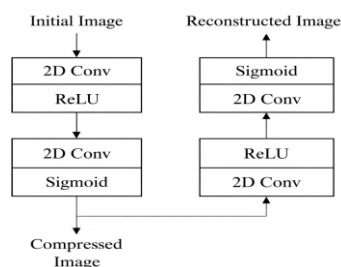


Fig 2 Topology of CAE

- **Encoder Stage:** The input MRI image is passed through 2D Convolution and ReLU layers to extract important spatial features and reduce redundancy.
- **Compression:** A 2D Convolution with Sigmoid activation generates a compressed (latent) representation that retains essential tumor-related information.
- **Decoder Stage:** The compressed image is expanded using 2D Convolution and ReLU layers to reconstruct spatial details.
- **Reconstruction Output:** A final Sigmoid layer produces the reconstructed image, which is compared with the input to minimize reconstruction loss.



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### 1. Convolutional Neural Network (CNN)

CNN is a basic and widely used deep learning model for image classification tasks. It automatically extracts features such as edges, textures, and shapes from input images. The model consists of convolution layers, pooling layers, and fully connected layers. These layers work together to learn patterns from MRI images and classify them into different categories. CNN does not require manual feature extraction, making it efficient for medical imaging tasks. However, since it is a relatively simple model, its performance may be lower compared to advanced architectures when dealing with complex datasets.

#### 1. CNN – VGG16

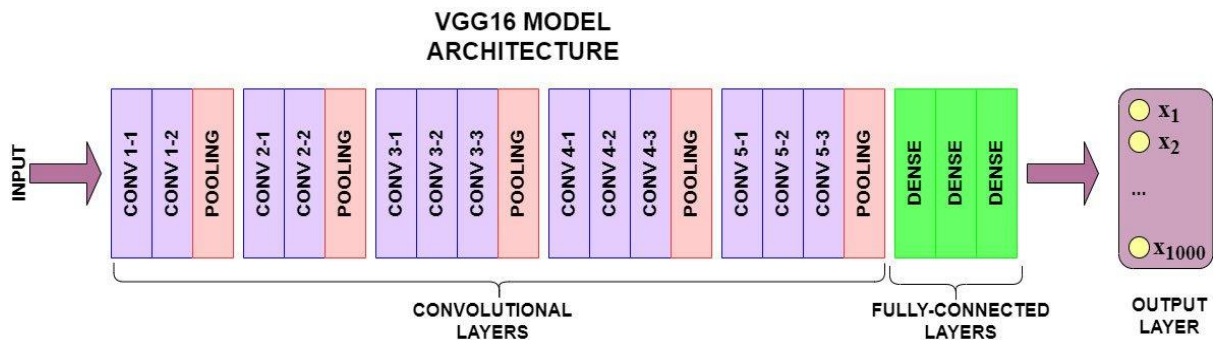


Fig 3 VGG16 architecture with CNN Mode

- VGG16 is a deep convolutional neural network (CNN) for image recognition consisting of 13 convolutional layers, 5 max-pooling layers, and 3 fully connected (dense) layers.
- **Convolutional Layers** : Use  $3 \times 3$  filters (stride 1) to extract features; arranged in 5 blocks with increasing filters (64  $\rightarrow$  512).
- **Max-pooling layers**: Use  $2 \times 2$  (stride 2) to reduce dimensions; placed after each convolutional block.
- **Fully connected layers**: Three dense layers, first two with 4096 units, for final classification.
- **ReLU**: Adds non-linearity in hidden layers to learn complex patterns.
- **Softmax**: Converts final outputs into class probabilities.

#### 2. CNN – VGG19



Fig.4 VGG19 architecture with CNN Mode

- **16 Convolutional Layers**: The 16 convolutional layers are grouped into five blocks with  $3 \times 3$  filters (64  $\rightarrow$  128  $\rightarrow$  256  $\rightarrow$  512  $\rightarrow$  512), using stride 1 and same padding to preserve spatial resolution.
- **5 Max Pooling Layers**: Each block ends with a  $2 \times 2$  max pooling layer that halves the feature map dimensions.
- **3 Fully Connected Layers**: After the final convolutional block and max pooling, the feature maps are flattened and fed into three fully connected layers.



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### IX. IMPLEMENTATION OF MODEL

The proposed system integrates a deep learning model with a web-based frontend for Brain Tumor detection. Initially, BT scan images are preprocessed by resizing, normalization, and data augmentation to improve model performance using CAE.

The classification model is developed using CNN, CAE architectures. Deep learning is applied using pre-trained weights, and the models are trained using the Adam optimizer with categorical cross-entropy loss. Among the models, CNN – VGG16 achieves the best performance and is selected for deployment.

For user interaction, a web-based frontend is developed using HTML, CSS, and JavaScript. The backend is implemented using Streamlit, where the trained model is loaded for prediction. Users can upload MRI images through the interface, and the system processes the image and provides instant detection results, indicating whether the Brain is normal or with Tumor along with the Patient Profile(Age group, gender).

This integration ensures a simple, efficient, and user-friendly system that can assist medical professionals in diagnosis.

### X. MODELS RESULTS

#### 1. CNN-VGG16

##### Confusion matrix for CNN

- The confusion matrix shows most predictions on the diagonal, indicating correct classification, with minor confusion between tumor classes.
- The model achieves 98% accuracy, performing best on normal images. Performance can be improved using data augmentation and deep learning models like CNN- VGG16.

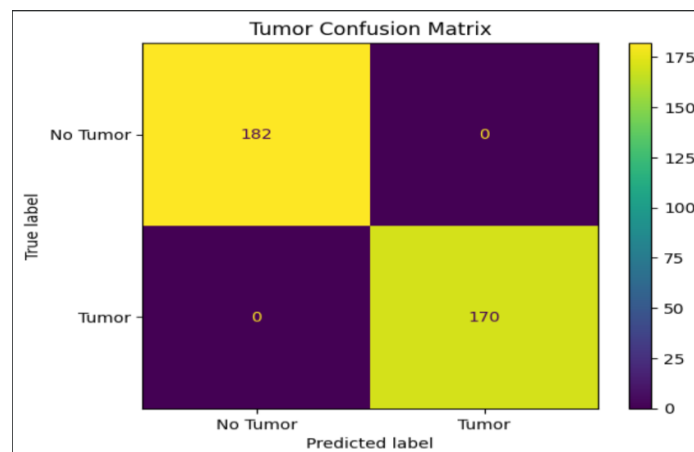


Fig 5 : Confusion matrix for CNN-VGG16

##### Classification Report for CNN

- This classification report shows that the VGG16 model achieved 100% accuracy with perfect precision, recall, and F1-score for all classes.
- Each class has equal support, so macro and weighted averages are also 1.00.



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```

... ● Tumor Classification Report
      precision    recall  f1-score   support

   No Tumor         1.00      1.00      1.00       182
    Tumor          1.00      1.00      1.00       170

 accuracy                   1.00       352
 macro avg              1.00      1.00      1.00       352
 weighted avg          1.00      1.00      1.00       352
    
```

Fig 6 : Classification Report for CNN-VGG16

### Graphs for CNN-VGG16

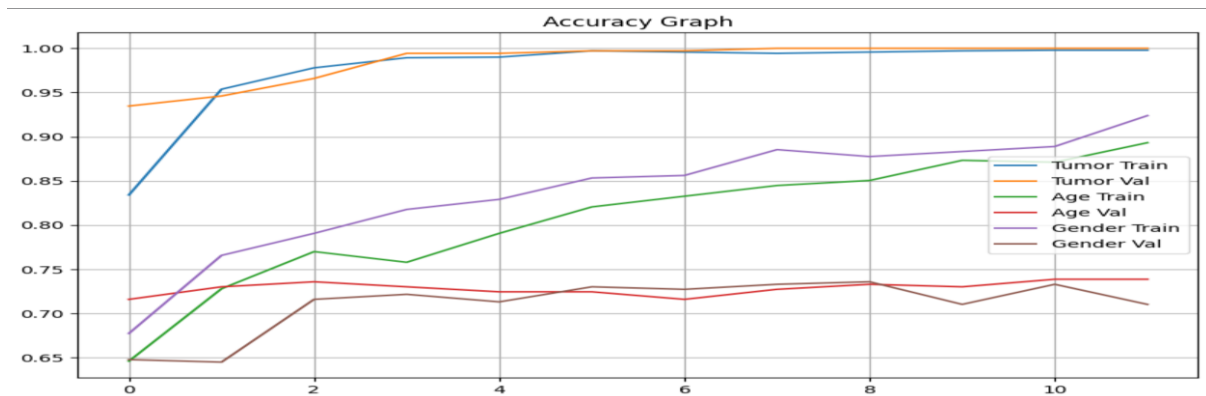


Fig 7 : Graphs for CNN-VGG16

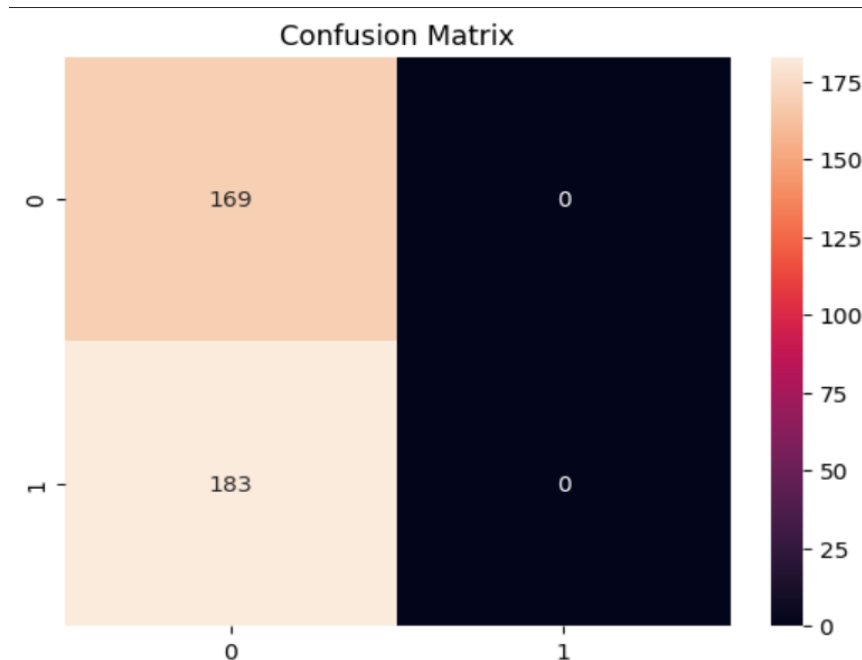
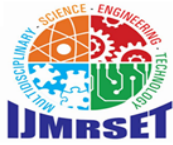


Fig 8 : Confusion Matrix for CNN-VGG19



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### Classification Report for CNN-VGG19

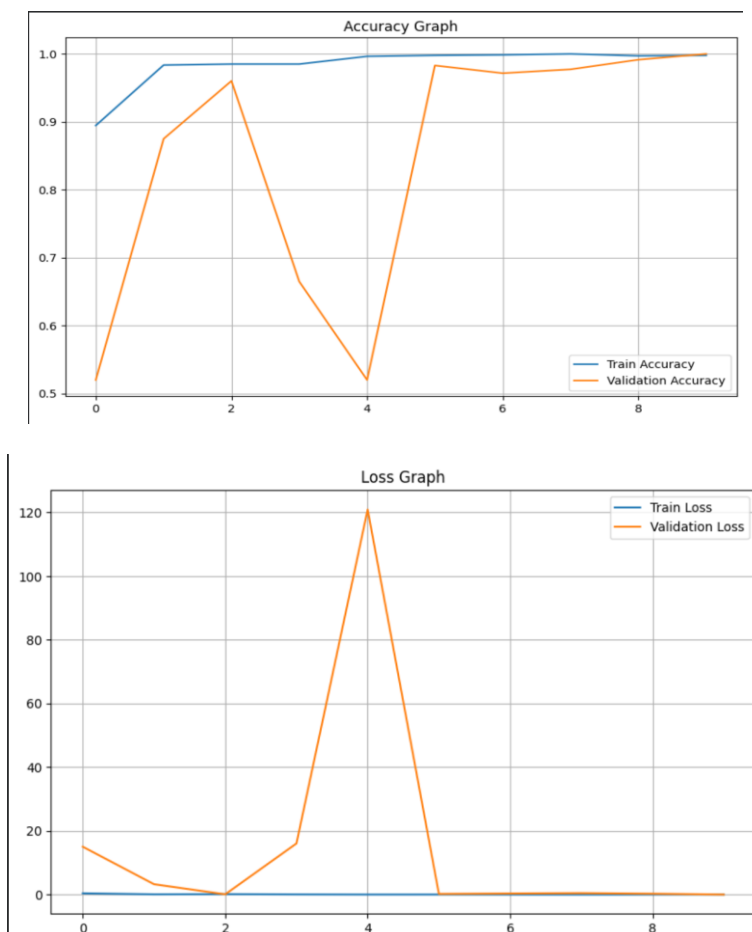
- This classification report shows the performance of the CNN- VGG19 model.
- The overall accuracy of the model is 96.33%, indicating good performance.
- For some cases it shows imbalance between precision and recall, meaning some cases are misclassified.
- Overall, the model performs well but can be improved for better cancer subtype detection.

	precision	recall	f1-score	support
0.0	1.00	1.00	1.00	169
1.0	1.00	1.00	1.00	183
accuracy			1.00	352
macro avg	1.00	1.00	1.00	352
weighted avg	1.00	1.00	1.00	352

Fig 9 : Classification Report for CNN – VGG19

Graphs for CNN-VGG19

Fig 10 : Graphs for CNN-VGG19





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### XI.WEB INTERFACE

The web application provides a simple interface for users to upload Brain MRI images and get predictions. After uploading, the system analyzes the image using the trained model and displays the detected cancer type along with a confidence score. The uploaded image is also shown for reference, making the process quick and easy to use.

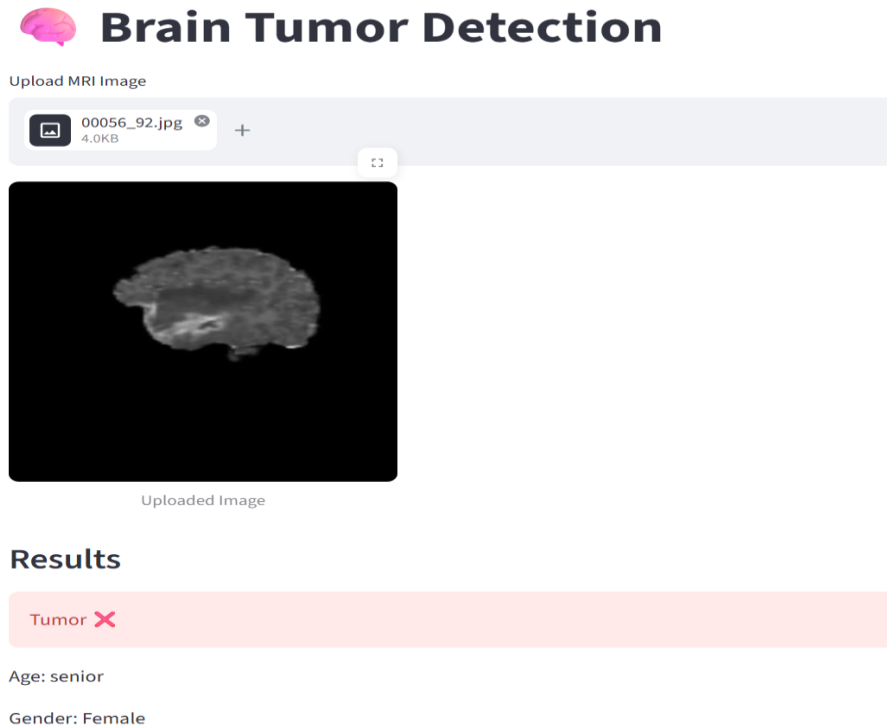


Fig 11 : WEB INTERFACE

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