



# BRAIN TUMOR PREDICTION USING MACHINE LEARNING

**Dhanya K<sup>1</sup>, Dr. P. Deepika<sup>2</sup>**

<sup>1</sup>Student, Department of Artificial Intelligence and Machine Learning, Dr. N.G.P. Arts and Science College, Coimbatore, Tamil Nadu, India

<sup>2</sup>Associate Professor, Department of Artificial Intelligence and Machine Learning, Dr. N.G.P. Arts and Science College, Coimbatore, Tamil Nadu, India

## ABSTRACT

Brain tumor prediction using machine learning has become an essential research area in medical image analysis due to the increasing demand for early, accurate, and automated diagnosis. Manual examination of MRI scans is time-consuming and prone to human error. This study proposes a machine learning-based system to predict and classify brain tumors from MRI data. The workflow includes image acquisition, preprocessing, feature extraction, model training, and prediction. Preprocessing techniques such as noise removal, normalization, and segmentation enhance image quality and highlight tumor regions. Extracted features train supervised learning models, enabling effective classification of normal and abnormal tissues. The proposed approach reduces dependency on manual interpretation and supports radiologists with fast, reliable results. Designed to be scalable and cost-effective, the system demonstrates the potential of artificial intelligence to improve healthcare outcomes, reduce diagnosis time, and enhance treatment planning.

**KEYWORDS:** Brain Tumor Prediction, Machine Learning, MRI, Medical Image Processing, Classification.

## 1. INTRODUCTION

Brain tumors are abnormal cell growths that disrupt brain function and can be fatal if not detected early. Traditional diagnosis relies on radiologists manually analyzing MRI scans, which is time-consuming and prone to variability. With the increasing volume of medical imaging data, automated systems are needed to assist clinicians with reliable predictions. Machine learning enables computers to learn patterns directly from data, improving diagnostic precision and reducing misinterpretation. MRI is widely used for brain tumor diagnosis due to its high contrast resolution, but raw images often contain noise and intensity variations. Preprocessing techniques such as filtering, normalization, and segmentation are applied to enhance image quality. Feature extraction captures characteristics like texture, shape, and intensity, which are crucial for classification. Supervised machine learning algorithms such as Support Vector Machines (SVM), Random Forests, and Convolutional Neural Networks (CNNs) have shown promising results. Deep learning approaches automatically extract high-level features, reducing manual effort. These systems minimize human error, reduce diagnosis time, and improve consistency.

## 2. THE LITERATURE STUDY

The literature on brain tumor prediction shows a shift from manual diagnosis to AI-driven methods. Initially, radiologists relied on manual interpretation of MRI and CT scans, which was accurate but slow and prone to human error. Early automated systems using image processing techniques like thresholding and edge detection struggled with complex tumor shapes and varying intensities. Later, traditional machine learning methods such as SVMs and Random Forests improved performance but required manual feature engineering, limiting adaptability. With the advent of deep learning, CNNs like AlexNet, VGGNet, and ResNet enabled automatic feature

extraction and achieved higher accuracy in tumor classification. More recent studies highlight lightweight models such as ShuffleNet and MobileNet, which balance efficiency and accuracy, making them suitable for real-time clinical use. However, gaps remain in scalability, interpretability, and integration with clinical reporting, which this project aims to address through a ShuffleNet-based framework

## 3. PROPOSED SYSTEM

The proposed system uses a deep learning model, specifically ShuffleNet, to predict brain tumors from MRI and CT scans in an automated and efficient way. The process begins with preprocessing to clean and standardize images, followed by segmentation to isolate tumor regions. ShuffleNet then performs feature extraction, learning complex patterns without manual intervention, and the model classifies tumors as benign or malignant. Finally, the prediction module provides results along with tumor size and location, supported by secure database management and clear reporting for clinicians. This system reduces human error, speeds up diagnosis, and ensures consistent accuracy, making it a practical AI-driven solution for healthcare.

## 4. METHODOLOGY

### Data Collection

MRI images collected from public datasets or hospital archives serve as the raw input for the system, providing the essential structural details of the brain required for analysis. The quality and diversity of these datasets are crucial, as clearer and more varied images enable the model to learn better patterns and improve its ability to make accurate predictions across different cases

### Preprocessing

Raw MRI scans often contain noise and intensity variations, so preprocessing is applied to improve quality and consistency. It removes distortions, normalizes pixel values, resizes images, and segments the brain region to highlight tumor areas, ensuring clean and focused data for accurate machine learning analysis.

### Feature Extraction

Feature extraction focuses on pulling measurable characteristics from MRI images that help in identifying tumors. Key features include texture, which shows irregular pixel patterns, shape, which captures the geometric outline of the tumor, and intensity, which highlights brightness differences between tissues. These extracted features are then used as inputs for machine learning algorithms to distinguish normal brain tissues from tumor-affected regions

### Model Training

Supervised learning algorithms are trained on labeled MRI datasets where images are tagged as “tumor” or “normal,” allowing the model to learn meaningful patterns. Methods like SVM, Random Forests, and CNNs are commonly used, with CNNs being especially effective as they automatically extract complex features. Through this training, the system becomes capable of accurately classifying new scans and detecting tumor regions.

### Prediction

Once trained, the model can analyze new MRI scans and classify them as “tumor present” or “no tumor.” This step

simulates real-world clinical use by providing quick and reliable predictions. It assists radiologists by reducing workload, speeding up decisions, and supporting consistent treatment planning.

### Evaluation

The model’s performance is measured using key metrics. Accuracy shows overall correctness, precision reflects how many predicted tumors were truly tumors, and recall measures the ability to detect tumors when present. A confusion matrix further details correct and incorrect classifications, ensuring reliable evaluation

## 5. RESULT AND DISCUSSION

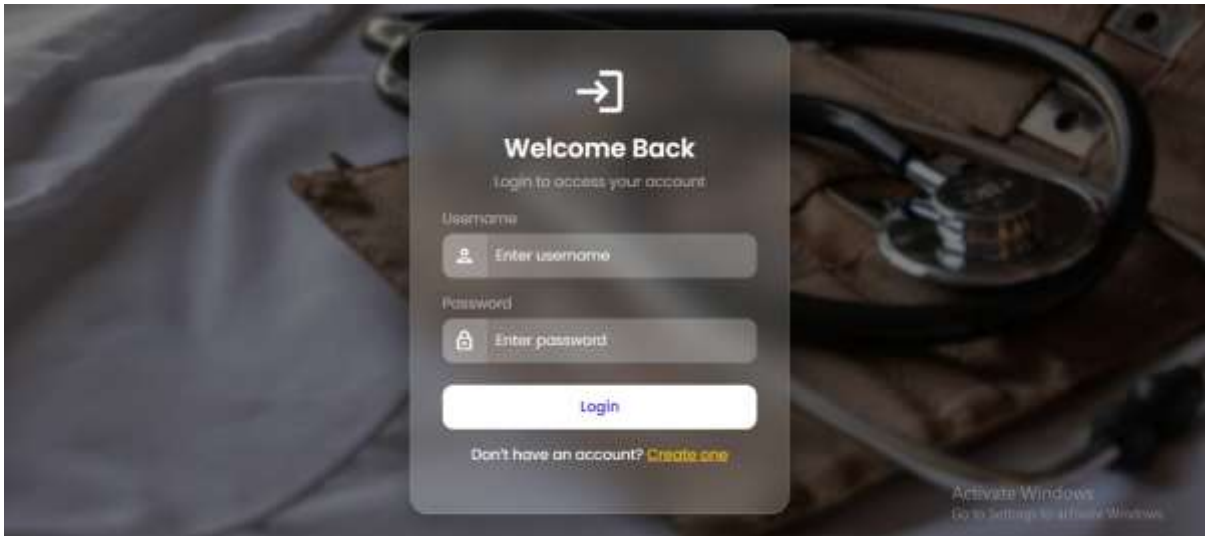
The proposed system demonstrates improved diagnostic accuracy compared to manual methods because automated preprocessing removes noise, normalizes intensity, and segments MRI scans to highlight tumor regions, while feature extraction captures texture, shape, and intensity patterns that make tumors more visible. These refined inputs allow machine learning classifiers such as SVM, Random Forests, and CNNs to learn complex patterns and deliver reliable predictions, reducing misinterpretation and minimizing human error. As a result, diagnosis time is significantly shortened, enabling faster clinical decisions and early detection of subtle tumors. Importantly, the system functions as a decision-support tool rather than a replacement for radiologists, assisting them by flagging critical regions and providing consistent predictions that enhance treatment planning, scalability in busy hospitals, and accessibility in resource-limited settings.



Fig No:1 Create Account

(The image shows a healthcare-themed account creation screen with a stethoscope and medical pouch in the background.

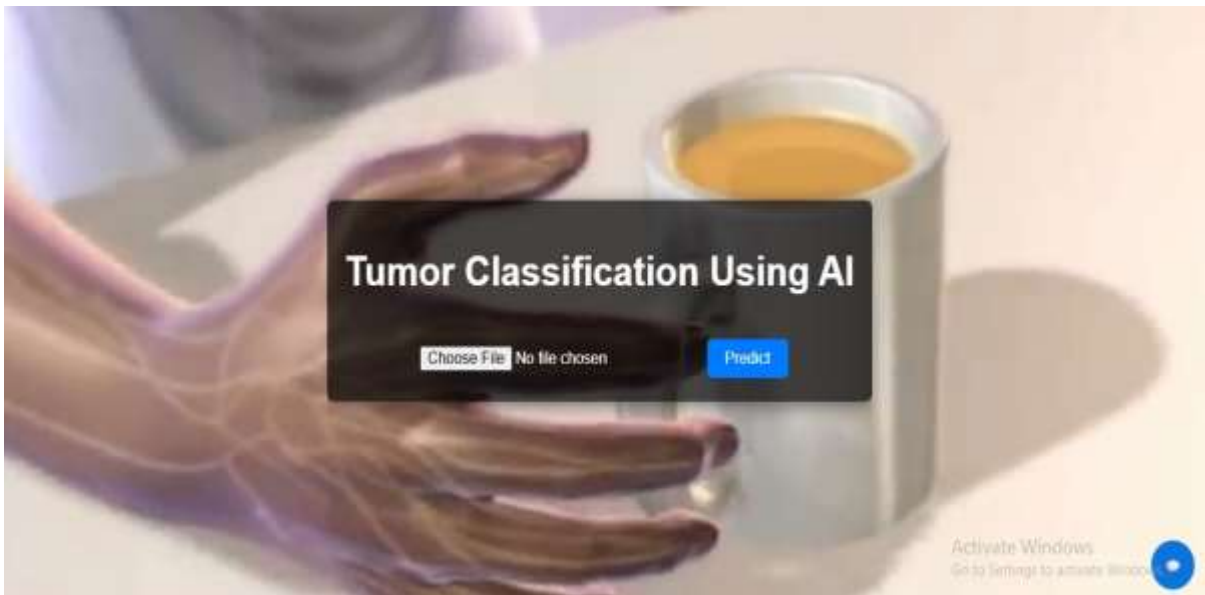
It features fields for username and password, a "Create Account" button, and a login link for existing users.)



**Fig No:2 User Login Interface**

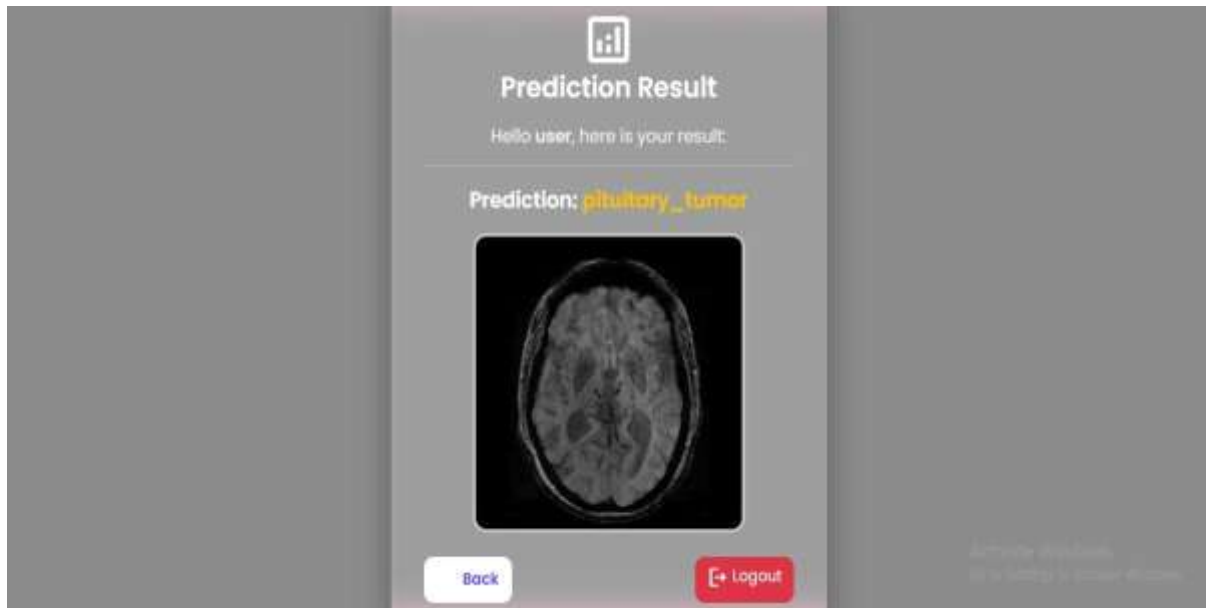
(The image shows a healthcare-themed login screen with a semi-transparent panel over a blurred background of a stethoscope and medical bag.

It includes fields for username and password, a "Login" button, and a link to create a new account.)



**Fig No:3 Tumor Classification using AI**

(The interface displays a tumor classification AI tool with options to upload medical files and predict results.)



**Fig No:4 Prediction Result**

(The interface displays a tumor classification AI tool with options to upload medical files and predict results. Its design combines clinical functionality with an anatomical-themed background for visual emphasis.)

## 6. CONCLUSION AND FUTURE WORK

The Brain Tumor Prediction System highlights the transformative role of machine learning in medical diagnostics by automating the detection and classification of brain tumors from MRI scans, reducing reliance on manual interpretation that is often time-consuming and error-prone. Through preprocessing, segmentation, feature extraction, and CNN-based classification, the system achieves high accuracy with minimal false results, while database and reporting modules ensure organized patient data management and interpretable outputs for clinicians. Looking ahead, integrating multi-modal imaging, advanced deep learning architectures, larger and more diverse datasets, and real-time processing can enhance accuracy and scalability, while cloud-based platforms, hospital system integration, and explainable AI will improve accessibility, transparency, and trust. Together, these advancements position the system as a foundation for next-generation AI-driven healthcare solutions that support early detection, personalized treatment, and improved patient outcomes worldwide.

## REFERENCES

### Bibliography

1. A. M. Hasan, H. A. Jalab, F. Meziane, H. Kahtan, and A. S. Al-Ahmad, "Combining deep and handcrafted image features for MRI brain scan classification," *IEEE Access*, vol. 7, pp. 79959–79967, 2019, [6].
2. R. A. Zeineldin, M. E. Karar, J. Coburger, C. R. Wirtz, and O. Burgert, "DeepSeg: Deep neural network framework for automatic brain tumor segmentation using magnetic resonance FLAIR images," *Int. J. Comput. Assist. Radiol. Surg.*, vol. 15, no. 6, pp. 909–920, Jun. 2020
3. R. V. Tali, S. Borra, and M. Mahmud, "Detection and classification of leukocytes in blood smear images: State of the

- art and challenges," *Int. J. Ambient Comput. Intell.*, vol. 12, no. 2, pp. 111–139, Apr. 2021
4. M. A. Queiroz, M. Hüllner, F. Kuhn, G. Huber, C. Meerwein, S. Kollias, G. von Schulthess, and P. Veit-Haibach, "Use of diffusion-weighted imaging (DWI) in PET/MRI for head and neck cancer evaluation," *Eur. J. Nucl. Med. Mol. Imag.*, vol. 41, no. 12, pp. 2212–2221, Dec. 2014
5. T. Rajesh, R. S. M. Malar, and M. R. Geetha, "Brain tumor detection using optimisation classification based on rough set theory," *Cluster Comput.*, vol. 22, no. S6, pp. 13853–13859, Nov. 2019.
6. Ostrom QT, Gittleman H, Truitt G, Boscia A, Kruchko C, Barnholtz-Sloan JS. CBTRUS Statistical Report: Primary Brain and Other Central Nervous System Tumors Diagnosed in the United States in 2011–2015. *Neuro Oncol* (2018) 20:iv1–86.
7. Louis DN, Schiff D, Batchelor T, Wen PY. *Classification and Pathologic Diagnosis of Gliomas*. In: *UpToDate*. Waltham, MA: Walters Kluwer Health (2017).
8. Louis DN, Perry A, Reifenberger G, Von Deimling A, Figarella-Branger D, Cavenee WK, et al. The 2016 World Health Organization Classification of Tumors of the Central Nervous System: A Summary. *Acta Neuropathol* (2016)
9. van den Bent MJ. Interobserver Variation of the Histopathological Diagnosis in Clinical Trials on Glioma: A Clinician's Perspective. *Acta Neuropathol* (2010)
10. Mousavi HS, Monga V, Rao G, Rao AUK. Automated Discrimination of Lower and Higher Grade Gliomas Based on Histopathological Image Analysis. *J Pathol Inform* (2015)