RESEARCH ARTICLE OPEN ACCESS

Deep Learning-Based Brain Tumor Detection and Classification Using MRI Images

Vinod Kumar Nain*, Amit Bohra, Pankaj jain****

*M.Tech Student, Department of Computer Science & Engineering, Global Institute of Technology, Jaipur

** Assistant Professor, Department of Computer Science & Engineering, Global Institute of Technology, Jaipur

ABSTRACT

Brain tumor detection is one of the most critical tasks in medical imaging because early and accurate diagnosis can significantly improve patient survival and treatment planning. Traditional diagnostic methods are often time-consuming and depend heavily on expert radiologists. Recent advancements in Artificial Intelligence (AI), Deep Learning (DL), and medical image analysis have enabled the development of automated systems for efficient brain tumor classification using Magnetic Resonance Imaging (MRI). This paper presents a deep learning-based framework for brain tumor detection and classification integrated with a user-friendly Graphical User Interface (GUI). The proposed methodology includes dataset collection, image preprocessing, normalization, data augmentation, convolutional neural network (CNN) model design, training, validation, and performance evaluation. The preprocessing stage improves image quality and enhances model generalization using techniques such as resizing, normalization, noise reduction, rotation, and flipping. The CNN model extracts hierarchical features from MRI images and classifies tumor and non-tumor cases effectively. Performance evaluation is carried out using accuracy, precision, recall, F1-score, and confusion matrix analysis. The integration of the trained deep learning model with a GUI developed using Python and Tkinter allows healthcare professionals to upload MRI images and obtain classification results in a simple and interactive manner. Experimental analysis demonstrates that deep learning and ensemble-based approaches provide high classification performance and reliable tumor detection. The proposed system offers a practical, accurate, and intelligent solution for supporting radiologists in early brain tumor diagnosis and clinical decision-making.

Keywords — Brain Tumor Detection, Hybrid Machine Learning, Ensemble Learning, MRI Classification, Deep Learning, Medical Imaging, Artificial Intelligence, Stacking Ensemble, Multilayer Perceptron, Tumor Prediction.

1. INTRODUCTION

The rapid advancement of Artificial Intelligence (AI), Information Technology (IT), and e-healthcare technologies has transformed modern medical practice by enabling the development of intelligent systems that support healthcare professionals in delivering efficient and accurate patient care [1], [2]. These technologies have become increasingly important in the diagnosis of complex neurological disorders, including brain tumors.

A brain tumor is characterized by the uncontrolled proliferation of abnormal cells within the brain or the central nervous system. Such abnormal growth can disrupt normal brain activity, leading to neurological impairments, cognitive dysfunction, and, in severe cases, life-threatening complications [3], [4]. Brain tumors may originate within the brain tissue itself, in which case they are classified as primary tumors, or they may result from the spread of cancer from other organs to the brain, commonly referred to as metastatic or secondary tumors [5]. Because brain tumors represent one of the most critical forms of cancer affecting the central nervous system, their early identification is essential for improving treatment effectiveness and reducing mortality.

Medical imaging plays a fundamental role in the diagnosis and evaluation of brain tumors. Commonly used imaging techniques include Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) [6], [7]. Among these modalities, MRI is considered the preferred choice because it provides superior soft tissue contrast and produces high-resolution images that clearly distinguish normal brain structures from abnormal tumor tissues. This capability enables more accurate detection, localization, and characterization of brain lesions, making MRI highly valuable in clinical diagnosis [8].

The histological grade and biological characteristics of a brain tumor are key factors in determining the appropriate treatment strategy and predicting patient prognosis. According to the World Health Organization (WHO), gliomas are classified into four grades based on their level of malignancy. Grade I and Grade II tumors are categorized as low-grade gliomas (LGGs), whereas Grade III and Grade IV tumors are classified as high-grade gliomas (HGGs). Patients diagnosed with HGGs generally have a poor prognosis, with an average survival period of approximately one to two years. In contrast, individuals with LGGs typically have a longer life expectancy, ranging from five to ten years. Figure 1 presents representative MRI images illustrating different grades of brain tumors.

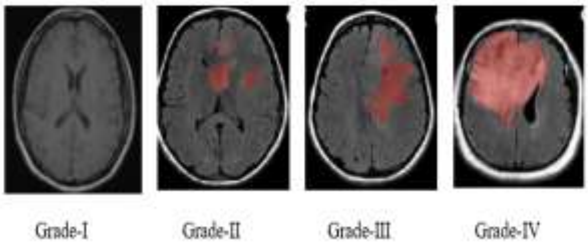

Figure 1: Brain Tumor Grades Images

Brain tumors are classified into two categories: malignant and benign. Benign tumors are non-neoplastic tissues that are harmless and lack the tendency to metastasize to other parts of the body. They can be removed surgically, but there is less chance of recurrence. Benign tumors also tend to have clearly defined borders and are not typically deeply embedded in brain tissue. As such, this feature makes their removal via surgery quite easy. Malignant tumors are cancers that arise from the brain. They grow faster than non-malignant tumors and are very harmful. Metastatic tumors spread to other parts of the body, also known as secondary tumors. This section reviews several methodologies and procedures used by various authors in the application of current brain tumor detection and classification techniques.

2. METHODOLOGY

The methodology section explains the systematic approach, which will be used to design and implement the proposed brain tumor detector system based on deep learning and a graphical user interface (GUI). This methodology aims to combine an advanced deep learning technology in medical image classification with the interactive software application that would be able to support radiologists and healthcare specialists in making their decisions.

The workflow of this project is described in this section and includes the process of datasets acquisition, data preprocessing, deep learning model architecture design, training, evaluation, and the development of the GUI. Visual representations are represented in place by figures and tables, which can subsequently be provided to support the thesis documentation.

Research Workflow

The methodology is a systematic workflow broken into 6 larger steps:

1. **Dataset Collection and Understanding:** MRI images were obtained using benchmark brain tumor datasets which consist of tumor and non tumor images to create a rich basis to train and evaluate the classification model.
2. **Preprocessing and Data Augmentation:** All the images were normalized and scaled to a consistent size and were pre-processed with normalization and noise removal; data augmentation methods (such as rotation and flipping) were used to enhance data variety and make the model more general.
3. **Model Architecture Design (Deep Learning):** A Convolutional Neural Network (CNN) was created which helped to extract hierarchical characteristics of the MRI images, and layers like convolution, pooling, dropout, and fully connected layers were used in order to effectively classify the images.
4. **Training and Validation Strategy:** The dataset was divided into training, validation and test subsets and the model was trained under the supervised learning strategy with early-stopping and cross-validation strategies to avoid over-fitting and guarantee high performance.
5. **GUI Application Development:** A GUI was created in Python, based on the Tkinter library, to enable the user (e.g., a doctor) to upload MRI images, execute the trained model, and display the classification results in a form accessible to users.
6. **Evaluation and Performance Analysis:** To test the system, the usual measures of accuracy, precision, recall and F1-score, and the confusion matrix analysis were evaluated to thoroughly test the performance of the model and its practical use.

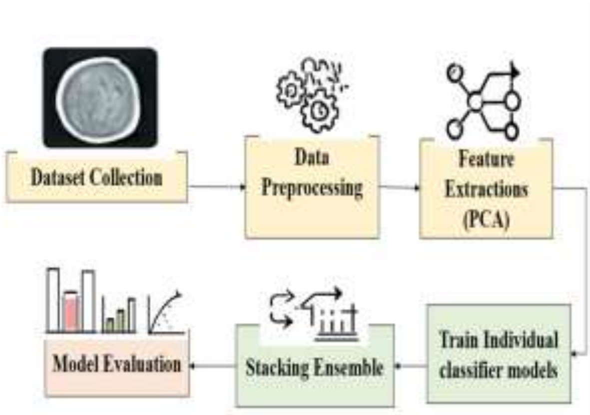

Figure 2: Overall Workflow of the Proposed Methodology

3. EVALUATION MATRICES

Evaluation Metrics

The standard classification measures were used to evaluate the model performance:

- **Accuracy** - Accuracy is the percentage of the correctly classified MRI images to all the samples considered. It measures the overall performance of the model in separating the tumor and non-tumor cases and the tumor subtypes. As much as precision is a simple metric, it might not be enough in unbalanced datasets where certain classes are overrepresented, so adding some metrics is essential. The measure of accuracy should be measured as in equation 1:

$$\text{Accuracy} = \frac{\text{Number of correctly classified samples}}{\text{Total Number of Samples}} * 100 \quad (1)$$

- **Precision** – Precision is used to measure the accuracy of the positive predictions of the model and is calculated as the number of the true positive classifications against the total of those predicted to be positive. It demonstrates how minimally false positives the model has, which is especially valuable in medical diagnostics to prevent the needless alarm and invasive methods of follow-up. The accuracy is high so that as the model indicates the existence of a tumor, the prediction is accurate. Precision value was determined by equation 2.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives+False Positives}} \quad (2)$$

- **Recall (Sensitivity)** – In recall, which is also known as sensitivity measures the ability of the model to detect real tumor cases with the correct cases by computing the ratio of the true positives to all real positive cases. High recall is very important in clinical practice because it will mean that majority of the tumor patients will not be missed. It is a measure of how well the model eliminates false negatives, which increases diagnostic safety. Recall assessment performed based on equation 3:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives+False Negatives}} \quad (3)$$

- **F1-Score** – The harmonic mean of precision and recall is the F1-score, which is a balanced measure considered to be a false positive and false negative. This composite metric as depicted in equation 4 is especially useful in imbalanced dataset where it helps to evaluate the trade-off between precision and recall. The fact that the F1-score is high means that the model is capable of reducing false tumor detection and false alarms on actual tumor cases.

$$\text{F1 Score} = \frac{\text{Recall} * \text{Precision}}{\text{Recall} + \text{Precision}} * 2 \quad (4)$$

- **Confusion Matrix** – The confusion matrix provides a class-wise table of all the predictions of the model and their true association with the labels, showing the true positives, true negatives, false positives and false negatives of each type of tumor. Such granular analysis allows the determination of certain misclassification patterns, including confusion of similar types of tumors, to further tune the model and interpret the clinical findings. It can be used as an overall diagnostic system to determine what is good and what is not so good in classification.

4. RESULTS AND DISCUSSION

The comparison of the results was performed with the existing Machine learning and deep learning models such as the Random Forest, Support Vector machine, XGBoost, LightGBM, and MLP, in order to prove the excellence of the Ensemble model offered.

Table 1: Comparative Analysis of Accuracy Across Models

Model	**Accuracy (%)**
Random Forest	86.06
XGBoost	87.90
Light-GBM	87.90
SVC	87.90
MLP	86.37
Stacking Ensemble	88.51
Voting Ensemble	87.28

Table 1 provides a comparative study of the accuracy of classification (percent) with different machine learning models used in detecting brain tumors. On the same note, figure 3 presents the different performance comparison of classifiers in the aspects of accuracy (%) terms. The findings indicate that the ensemble models namely the Stacking Ensemble were the most accurate models with a performance of 88.51, better than the other traditional classifiers of the random forest, XGBoost, Light-GBM and SVC, which showed similar performance at 86-88.

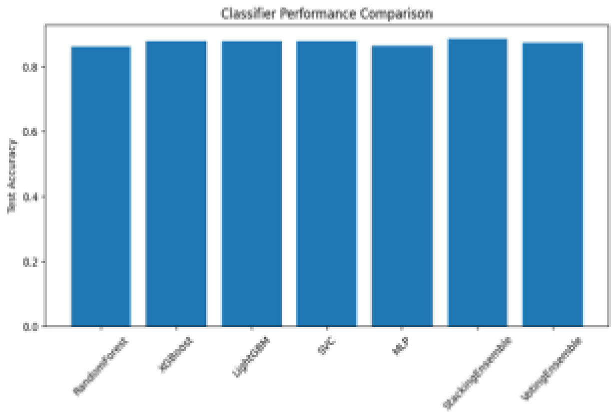

Figure 3: Classifier Models Performance Comparison

Performance was also high by the Voting Ensemble which had an accuracy of 87.28, more than the other models like the MLP (86.37%). This indicates the benefit of using a combination of multiple classifiers to tap into their complementing capabilities leading to improved predictive capability and robustness. The results confirm that ensemble learning methods can be useful to improve the accuracy of the brain tumor classification as compared to single models, which will be more reliable in clinical use.

5. CONCLUSION

This paper presented a comprehensive deep learning-based framework for brain tumor detection and classification using MRI images integrated with an interactive GUI application. The proposed methodology combined image preprocessing, data augmentation, CNN-based feature extraction, supervised training, and performance evaluation to develop an accurate and reliable diagnostic system. Standard evaluation metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis demonstrated the effectiveness of the proposed approach in identifying tumor and non-tumor cases. The integration of the trained deep learning model with a user-friendly GUI enhances the practical usability of the system for healthcare professionals and medical researchers. The results indicate that deep learning and ensemble-based techniques can significantly improve classification accuracy and support early diagnosis of brain tumors. The proposed system has strong potential for real-world clinical applications by assisting radiologists in fast, intelligent, and reliable medical image analysis.

REFERENCES

[1] S. AlZu'bi, D. Aqel, and M. Lafi, "An intelligent system for blood donation process optimization-smart techniques for minimizing blood wastages," Clust. Comput. J. NETWORKS Softw. TOOLS Appl., vol. 25, no. 5, pp. 3617–3627, Oct. 2022

[2] A. Gautam, C. Bakliwal, R. Ajmera, D. K. Dharamdasani, and R. Bhardwaj, "Predicting Analysis of Heart Attack Risk Using Machine Learning Algorithms and Deep Neural Networks," in Data Science and Exploration in Artificial Intelligence, pp. 396-406, 2025.

[3] J. Gowrishankar, I. Alam, V. S. Badiger, I. Soni, and M. S. Anwar, "A Hybrid CNN-RNN Model for Accurate Detection of Malignant Brain Tumors," pp. 1776–1781, 2025,

[4] D. K. Dharamdasani, K. Sharma, R. Ajmera, and A. Raj, "Exploring the Convergence of Neurophysiological and Behavioral Data: A Multi-model, Multi-database Approach to ADHD Diagnosis," in Lecture Notes in Networks and Systems, vol. 1468, 2026.

[5] Jason, F. Venesius, Y. Sie, R. Fredyan, and H. Pranoto, "Deep Learning-Based Brain Tumor Prediction: An Analysis of Performance Evaluation of Convolutional Neural Network," in 2023 15th International Congress on Advanced Applied Informatics Winter (IIAI-AAI-Winter), 2023, pp. 205–208.

[6] E. Akpinar, B. Hangun, M. Oduncuoğlu, O. Altun, Ö. Eyecioğlu, and Z. Yalçın, "Quantum-Enhanced Classification of Brain Tumors Using DNA Microarray Gene Expression Profiles," 2025.

[7] J. Narasimharao, S. Mubeen, V. Santosh Kumar, M. Soujanya, M. Nagaraju Naik, and A. Veerababu, "A Unique Method Using Deep Learning to Detect Brain Tumors and Performance Enhancement," Lect. Notes Networks Syst., vol. 1229 LNNS, pp. 370–379, 2025.

[8] S. K. Mathivanan, S. Sonaimuthu, S. Murugesan, H. Rajadurai, B. D. Shivahare, and M. A. Shah, "Employing deep learning and transfer learning for accurate brain tumor detection," Sci. Rep., vol. 14, no. 1, p. 7232, 2024.

[9] G. K. Soni, A. Rawat, S. Jain and S. K. Sharma, "A Pixel-Based Digital Medical Images Protection Using Genetic Algorithm with LSB Watermark Technique", Springer Smart Systems and IoT: Innovations in Computing. Smart Innovation, Systems and Technologies, Vol. 141, pp. 483-492, 2020.

[10] S. A. Saiyed, N. Sharma, H. Kaushik, P. Jain, G. K. Soni and R. Joshi, "Transforming portfolio management with AI and ML: shaping investor perceptions and the future of the Indian investment sector," Parul University International Conference on Engineering and Technology 2025 (PiCET 2025), pp. 1108-1114, 2025.

[11] A. Sharma and K. Gautam, "Flood prediction using machine learning technique," 2nd International Conference on Pervasive Computing Advances and Applications (PerCAA 2024), pp. 319-327, 2024.

[12] R. Ajmera et al., "Prediction analysis for diabetic patients using clustered based classification," Journal of Emerging and Innovative Research, vol. 5, no. 7, pp. 770–775, Jul. 2018.

[13] H. Kaushik, I. Yadav, R. Yadav, N. Sharma, P. K. Sharma and A. Biswas, "Brain tumor detection and classification using deep learning techniques and MRI imaging," Parul University International Conference on Engineering and Technology 2025 (PiCET 2025), pp. 1453-1457, 2025.

[14] N. Mathur, R. Ajmera, and J. S. Yadav, "Cause Effect Testing of Flu in Medical Sciences," in Proc. IEEE Int. Conf. Computing, Communication and Automation (ICCCA), 2017.

[15] R. Misra, N. Sharma, G. K. Soni, H. Arora, S. Chauhan and A. Biswas, "A Hybrid and Ensemble Machine Learning Framework for Enhanced Brain Tumor Detection," 2026 International Conference on Electronics and

Renewable Systems (ICEARS), pp. 1583-1588, 2026.

[16] A. B. Chincholkar and R. Ajmera, "Challenges and Gaps in Tuberculosis Diagnosis: Toward Robust Diagnostic Frameworks for Severity Assessment Using Microscopic Sputum Smears," in Proc. Engineering Data Analytics and Management Conference (EAMCON), pp. 560-577, 2025.