

ENHANCED CNN ALGORITHM FOR BRAIN TUMOR DETECTION AND CLASSIFICATION

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ABSTRACT

Brain tumors are abnormal growths in brain tissues that can be life-threatening if not detected and treated at an early stage. Early detection and classification of brain tumors are crucial in improving patient survival rates and treatment effectiveness. This paper implements a Convolutional Neural Network (CNN)-based deep learning model to detect and classify brain tumors from MRI images into three categories: Glioma, Pituitary, and No Tumor.

The proposed system follows a structured approach, including data preprocessing, model training, and real-time prediction through a Flask web application. The system classifies MRI images and provides a confidence score, urgency level, suggested treatment, and a timeline for medical intervention. The model is trained on an extensive dataset of MRI scans and optimized for accurate classification. The final application is deployed using Flask, allowing users to upload MRI images and receive real-time results. This paper is a valuable tool for assisting radiologists and medical professionals by providing an automated and efficient approach to detecting and classifying brain tumors.

Keywords: Brain tumor detection, CNN, MRI image classification, model training, flask web application.

1. INTRODUCTION

Brain tumors are among the most serious medical conditions, often requiring early diagnosis and precise classification for effective treatment. Medical imaging, particularly Magnetic Resonance Imaging (MRI), is widely used for brain tumor detection. However, manual diagnosis is time-consuming and prone to human error. Integrating machine learning (ML) and deep learning (DL) can significantly enhance tumor detection, classification accuracy, and efficiency.

This paper introduces a CNN-based deep-learning model for detecting and classifying brain tumors into three different categories. The model is trained using a labeled dataset of MRI images. The developed system is deployed as a web-based application using Flask, allowing users to upload MRI images and receive predictions with additional insights like urgency level, suggested treatment, and a timeline for treatment. built-in; examples of the type styles are provided throughout this document and are identified in italic type, within parentheses, following the example. Some components, such as multi-leveled equations, graphics, and tables, are not prescribed, although various table text styles are provided.

2. LITERATURE REVIEW

The detection and classification of brain tumors using deep learning methods, particularly Sparkle Neural Networks (CNN), has been carefully studied in recent years. Various methodologies have been proposed to enhance the accuracy of segmentation and classification effectiveness in the analysis of MRI-based tumors. Pereira et al. (2016) [1] implemented a deep learning-based approach utilizing CNNs for brain tumor. This study shows that deep CNNs can outperform traditional automated learning techniques in terms of accuracy and recall. Chan et al.. (2018) [2] introduced an automated pipeline of deep learning to detect and classify brain tumors during MRI. The study used an increase in data and pre-formed networks to increase the precision of the classification. Havaei et al.. (2017) [3] introduced a CNN-based two-phase model for brain tumor segmentation. Their model used a hierarchical approach. This study showed a significant improvement in segmentation accuracy compared to conventional methods. While previous studies have significantly contributed to brain tumor segmentation and classification, this work introduces several novel enhancements. Integration of Flask-based Web Application Unlike most previous research focusing solely on model training and evaluation, our work implements a user-friendly web interface for real-time tumor detection and classification. Enhanced Visualization and User Interaction Our system includes graphical visualization of classification confidence using Matplotlib and animated confidence level graphs powered by Chart.js, making results more interpretable. Dynamic Report Generation We introduce an automated PDF report generation module that provides a structured summary of the detection results, including patient details, tumor type, confidence scores, and recommended treatments.

3. METHODOLOGY

3.1 Dataset

The dataset utilized in this research was gathered from the Kaggle website, a well-known resource for machine learning datasets. It comprises MRI scans of brain tumors divided into three categories based on medical assessments. This dataset is frequently employed for training deep learning models aimed at tumor detection and classification. The three types of brain tumors in the dataset are:

Glioma Tumor:

This type of tumor originates in the glial cells of the brain or spinal cord. Glioma is one of the most common and aggressive brain tumors, requiring accurate diagnosis. MRI images of glioma tumors show irregular growth patterns in different regions of the brain.

Pituitary Tumor:

These tumors develop in the pituitary gland, which is responsible for hormone regulation. Pituitary tumors are mostly benign (non-cancerous) but can affect bodily functions due to hormonal imbalance. MRI scans for pituitary tumors show a well-defined growth near the base of the brain.

No Tumor (Healthy Brain):

MRI scans without any visible tumors are categorized as "No Tumor." These images help the model differentiate between normal brain structures and abnormal growths.

4. MODEL ARCHITECTURE

To categorize MRI images into Glioma, Pituitary, and No Tumor, a Convolutional Neural Network (CNN) is implemented. A CNN is a deep learning architecture specifically tailored for image-related tasks, allowing it to autonomously extract significant features from images. The Model Architecture diagram using CNN is as shown in Fig.1

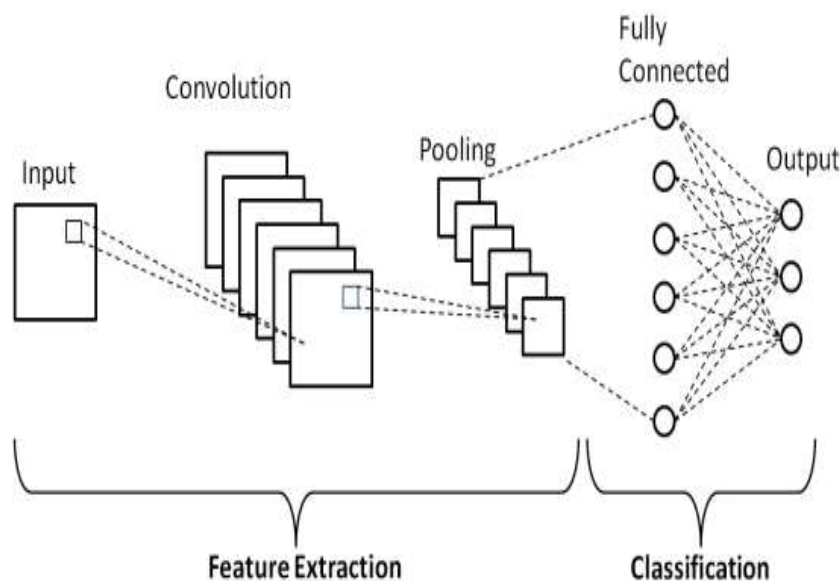


Figure 1: Model Architecture

- **Input Layer:** The CNN model takes an MRI image sized 224×224 pixels with 3 color channels (RGB) as input. The image is introduced into the network, which identifies key features necessary for classification.
- **Convolutional Layer:** These layers utilize filters (kernels) to analyze the image and recognize patterns such as edges, textures, and tumor outlines. The initial convolutional layer identifies fundamental edges and shapes, while subsequent layers capture more intricate tumor-related patterns. The ReLU (Rectified Linear Unit) activation function is employed to introduce non-linearity, enabling the network to learn complex features.
- **Pooling Layer:** Following each convolutional layer, max pooling is performed to minimize the dimensions of the feature maps. This process decreases computation time while preserving the most critical features. Pooling ensures that minor changes in the image's position do not compromise classification accuracy.
- **Fully Connected Layer:** The dense layers analyze the extracted features and categorize the MRI scans into one of the three classes. The final fully connected layer employs the Softmax activation function to produce probabilities for each class (Glioma, Pituitary, or No Tumor).

IMPLEMENTATION

The implementation of the Brain Tumor Detection and Classification System involves training a Convolutional Neural Network (CNN) on an MRI dataset containing three tumor categories: Glioma, Pituitary, and No Tumor. The model is built using TensorFlow and Keras, with image preprocessing techniques such as resizing, normalization, and data augmentation applied to improve generalization. The trained model is deployed using Flask, creating a web-based interface where users can upload MRI scans for real-time tumor detection. (Fig.2)



Figure 2: Web Interface

The system processes the image, classifies the tumor, and displays results with confidence scores and a bar graph visualization using Matplotlib and Chart.js. Additionally, a report generation module enables users to download a PDF report containing diagnosis details. The entire implementation ensures a user-friendly, efficient, and scalable solution for automated brain tumor classification.

5. RESULT AND DISCUSSION

The Tumor Detection and Classification System effectively categorizes MRI images into three types: Glioma, Pituitary, and No Tumor. The Convolutional Neural Network (CNN) model attained a high level of accuracy on the test set, proving its capability to extract important features from MRI scans. The system includes a Flask-based web application that allows users to upload MRI images and obtain real-time classification outcomes. (fig.3)



Figure 3: Web interface of the Brain Tumor Detection System, allowing users to upload MRI images for classification. In addition to identifying the tumor type, the model presents the confidence level of its predictions and visualizes the results using a bar graph. (fig.4) A comprehensive medical report is also generated in PDF format, which outlines the diagnosis and suggests suitable treatments.

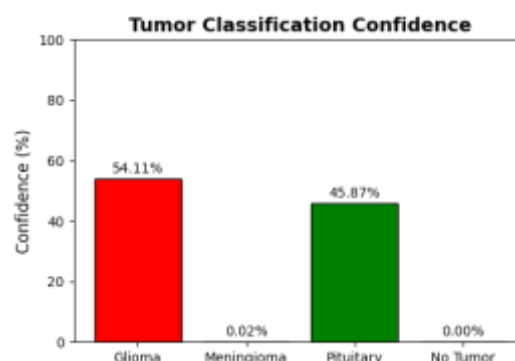


Figure 4: Graph Visualization

The findings emphasize the promise of deep learning in medical imaging through the automation of tumor identification and classification. In comparison to conventional manual diagnostic techniques, the CNN-based method delivers quicker, more reliable, and less error-prone outcomes. Nonetheless, the effectiveness of the model is affected by factors like the quality of the dataset, image resolution, and the parameters used during model training. While the existing system shows a high level of accuracy, there are opportunities for enhancement by enlarging the dataset, utilizing additional data augmentation methods, and optimizing hyperparameters. Furthermore, the performance could be improved by incorporating ensemble models or hybrid architectures. Future upgrades might also involve the integration of explainable AI methods to boost trust and clarity for healthcare professionals.

6. CONCLUSION

All the suggested AI-driven Brain Tumor Detection and Classification Systems highlights the capacity of deep learning in medical imaging by automating tumor diagnosis with notable precision. Leveraging Convolutional Neural Networks (CNNs), the system effectively categorizes MRI scans into Glioma, Meningioma, Pituitary, and No Tumor, offering a confidence score along with a visual representation of the predictions. The Flask-based web application improves accessibility, enabling users to upload MRI images, obtain real-time classification results, and download a comprehensive medical report in PDF format. This system can support radiologists and healthcare professionals by minimizing diagnostic errors and enhancing early detection rates, ultimately resulting in improved treatment outcomes. Future enhancements might concentrate on increasing the dataset size, refining model architecture, and incorporating explainable AI methods to boost reliability and clarity in clinical use.

7. REFERENCES

- [1] S. Pereira, A. Meier, V. Alves, C. Silva (2016) – *"Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images"*, IEEE Transactions on Medical Imaging.
- [2] K. Chang, G. Beers, M. Bai, R. Brown (2018) – *"Automated Deep Learning for Detection and Classification of Brain Tumors in MRI Scans"*, .
- [3] M. Havaei, A. Davy, D. Warde-Farley (2017) – *"Brain Tumor Segmentation with Deep Neural Networks"*, This paper presents a two-phase CNN-based model for accurate brain tumor detection.
- [4] R. Kamnitsas, C. Ledig, V. Newcombe (2017) – *"Efficient Multi-Scale 3D Convolutional Neural Networks for Brain Tumor Segmentation"*, IEEE Transactions on Medical Imaging.
- [5] S. Bakas, M. Reyes, T. Burns (2018) – *"Identifying Brain Tumors in MRI Scans Using AI and Deep Learning Models"*,
- [6] J. Long, E. Shelhamer, T. Darrell (2015) – *"Fully Convolutional Networks for Semantic Segmentation"*, IEEE Conference on Computer Vision and Pattern Recognition (CVPR).
- [7] G. Litjens, T. Kooi, B. Ehteshami Bejnordi (2017) – *"A Survey on Deep Learning in Medical Image Analysis"*, Medical Image Analysis.