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Automated Classification of Brain Tumors in MRI Images using Convolutional Neural Networks

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Abstract: Brain tumours are one of the most critical neurological disorders, and their early detection is essential for effective treatment and improved patient prognosis. Magnetic Resonance Imaging (MRI) is the standard imaging technique used for diagnosis; however, manual interpretation is time-consuming and prone to human error. This paper presents NEUROCARE, a desktop-based intelligent diagnostic system for brain tumor detection using a custom Convolutional Neural Network (CNN). The system is designed to classify MRI images into distinct categories, including Glioma, Meningioma, Pituitary tumor, and No Tumor. After evaluating various deep learning architectures, our final custom CNN model achieved a test accuracy of 93.82% with a test loss of 0.1971. The NEUROCARE application integrates this model into a user-friendly graphical user interface (GUI) built with Tkinter, offering functionalities such as patient history tracking and automated PDF report generation. This system aims to serve as an accessible and effective tool to assist radiologists in delivering faster and more accurate diagnoses.
Keywords: Brain Tumor Detection, Computer-Aided Diagnosis, Convolutional Neural Networks (CNN), Deep Learning, Medical Image Classification, MRI, NEUROCARE.

I. INTRODUCTION

Brain tumors represent a critical global health challenge due to their high mortality rate and the complexity involved in diagnosis and treatment. These tumors result from abnormal growth of cells within the brain or its surrounding structures and can be either malignant or benign. Early and accurate detection is essential, as late-stage diagnosis often leads to limited treatment options and reduced survival rates. Magnetic Resonance Imaging (MRI) is the most commonly used diagnostic imaging tool for detecting brain abnormalities, including tumors. However, interpreting MRI scans requires expert radiologists and is a time-consuming and error-prone process, particularly in resource-constrained or remote areas where access to qualified medical personnel may be limited.

This study introduces NEUROCARE, a machine learning-based desktop application designed to assist in the automated detection and classification of brain tumors using MRI images. The goal is to enhance diagnostic accuracy and reduce the dependence on manual evaluation. Advances in artificial intelligence, particularly deep learning, have paved the way for highly accurate image classification systems. Convolutional Neural Networks (CNNs), a type of deep learning architecture, are especially well-suited for analyzing visual data and have demonstrated considerable success in medical imaging tasks.

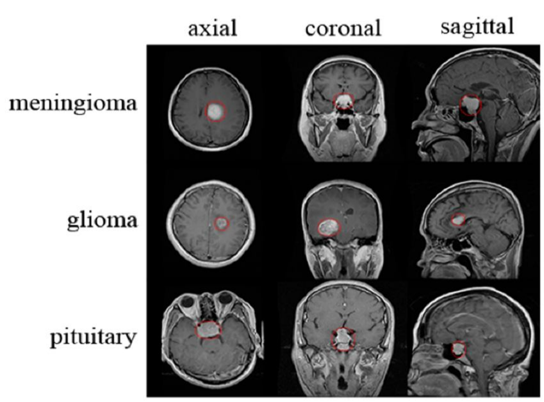


Fig 1. Various Types of Brain Tumors
Image courtesy: MDPI

CNNs are capable of learning complex features from MRI images that correlate with different types of brain tumors. By training on a large dataset of labeled MRI scans, the model can generalize well to unseen cases, enabling automatic classification with high precision. This project also evaluates various deep learning models, including VGG-16, ResNet, DenseNet, and InceptionNet, to determine the most effective architecture. The final model, a custom CNN, achieved a test accuracy of 93.82% and a test loss of 0.1971, highlighting its effectiveness. The NEUROCARE application integrates this model into a user-friendly graphical interface developed using Tkinter, making it suitable for clinical use in both urban and rural healthcare environments.

II. LITERATURE REVIEW

H. Mohsen et al. [1] have reported *"Classification using Deep Learning Neural Networks for Brain Tumors,"* where they proposed a hybrid method combining Discrete Wavelet Transform (DWT) for feature extraction with Deep Neural Networks (DNN) for classification. Their system classified MRI scans into normal, glioblastoma, sarcoma, and metastatic bronchogenic carcinoma categories, showing that integrating image processing with deep learning significantly enhances classification accuracy.

H. Byale et al. [2] have demonstrated *"Automatic Segmentation and Classification of Brain Tumor using Machine Learning Techniques,"* focusing on determining the malignancy of brain tumors through an end-to-end system. They used adaptive median filtering for preprocessing, Gaussian Mixture Models for segmentation, and GLCM features for extraction, followed by neural network-based classification. Their approach highlights the diagnostic power of layered machine learning methodologies.

S. Basheera and M. Satya Sai Ram [3] presented *"Classification of Brain Tumors Using Deep Features Extracted Using CNN,"* where they used an enhanced ICA mixture model for tumor segmentation and a CNN for extracting deep features. Their classification system demonstrated high performance in identifying normal scans and multiple tumor types, reinforcing the reliability of CNNs in feature-rich medical images.

F. P. Polly et al. [4] have investigated *"Detection and Classification of HGG and LGG Brain Tumor Using Machine Learning,"* utilizing k-means clustering for segmentation and a combination of DWT and PCA for feature extraction and reduction. Their study provides a structured approach for differentiating tumor grades, crucial for targeted treatment.

M. M. Badža and M. C. Barjaktarović [5] explored *"Classification of Brain Tumors from MRI Images Using a Convolutional Neural Network,"* testing CNN performance on imbalanced datasets using multiple cross-validation methods. Their results confirmed that proper validation and data augmentation improve model robustness across different tumor types.

J. Amin et al. [6] authored *"Brain Tumor Detection and Classification Using Machine Learning: A Comprehensive Survey,"* offering a broad overview of deep learning architectures used in medical imaging such as CNNs, 3D-CNNs, U-Net, and WRN-PPNet. This survey emphasizes the evolving nature of diagnostic algorithms and the need for model explainability in healthcare.

III. ALGORITHMS

The primary objective of this research is to develop a robust and accurate automated system for the classification of brain tumours using MRI scans. To accomplish this, we evaluated both traditional machine learning and deep learning techniques, ultimately selecting a convolutional neural network (CNN) for its superior performance and end-to-end learning capability. This section outlines the rationale behind our methodological choices and describes the architecture of the final implemented system.

The classification of brain tumours from images can be approached through two general paradigms: traditional machine learning with handcrafted features, and deep learning methods that automatically learn features from data. Traditional approaches typically involve a two-step process: extracting engineered features from segmented regions of interest (ROIs) in the MRI scans, and then applying a machine learning classifier. Commonly used features include textural attributes (e.g., contrast, correlation, homogeneity from GLCM), shape descriptors (e.g., area, perimeter, eccentricity), and intensity-based statistics (e.g., mean, standard deviation, skewness).

These features are then fed into classification algorithms such as Support Vector Machines (SVM) and Random Forests. SVMs work by identifying an optimal hyperplane that separates the classes in a high-dimensional feature space, often using kernel functions for non-linear boundaries. Random Forests, on the other hand, aggregate predictions from multiple decision trees to make robust, ensemble-based classifications and are known for their resistance to overfitting and ability to handle high-dimensional data. However, both methods are heavily reliant on the quality and relevance of the manually extracted features, which can be limiting.

In contrast, deep learning offers an integrated, end-to-end solution by learning hierarchical features directly from raw input data. Convolutional Neural Networks (CNNs), in particular, have emerged as state-of-the-art tools for image classification tasks, including medical imaging. In this study, we adopted a CNN-based architecture for its ability to automatically learn discriminative features relevant to tumour classification.

CNNs possess several advantages over traditional approaches. They eliminate the need for manual feature engineering, thereby reducing bias and workload. The architecture inherently captures spatial hierarchies within images, learning simple patterns like edges and textures in early layers, and complex structures such as tumour morphology in deeper layers. Moreover, CNNs have consistently demonstrated higher classification performance across a variety of visual recognition benchmarks.

Our implemented CNN model accepts pre-processed MRI scans resized to 150×150 pixels with three colour channels. The architecture consists of a series of four convolutional blocks. Each block includes a 2D convolutional layer with a 3×3 kernel and ReLU activation, followed by a 2×2 max pooling layer. The number of filters in these layers increases progressively from 32 to 128, allowing the network to capture increasingly complex features while reducing spatial dimensionality.

Following the convolutional base, the extracted feature maps are flattened and passed into a fully connected dense layer with 512 neurons and ReLU activation. A dropout layer with a rate of 0.5 is applied for regularization to mitigate overfitting. Finally, a dense output layer with four neurons—corresponding to the tumour classes (Glioma, Meningioma, Pituitary, No Tumour)—uses a softmax activation to produce class probabilities.

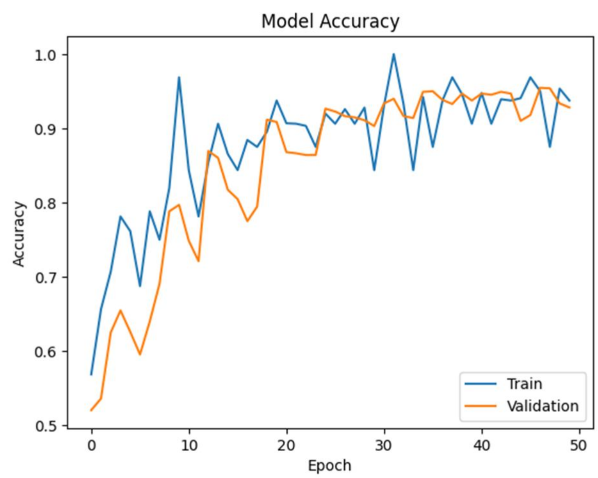
This CNN architecture provided the foundation for NEUROCARE, enabling accurate, automated classification of brain tumours and facilitating its integration into a clinical support tool with real-time prediction capabilities.

IV. RESULTS AND DISCUSSIONS

This section presents the empirical results of the trained Convolutional Neural Network (CNN) model. We provide a comprehensive analysis of its performance, both overall and on a per-class basis. The discussion interprets these findings, highlighting the model's strengths and weaknesses, its clinical relevance, the limitations of this study, and directions for future research.

A. Overall Model Performance

The model was trained for 50 epochs, and its performance was monitored on both the training and a hold-out test set. The training process exhibited stable convergence, as illustrated by the accuracy and loss curves in **Figure 2**.



The validation accuracy closely tracked training accuracy before reaching a plateau, indicating that the use of data augmentation and dropout was effective in mitigating significant overfitting. The final performance metrics on the test dataset are summarized in Table 2.

Table 2: Overall Model Performance on the Test Dataset

Metric	Training Set	Test Set
Accuracy	98.2%	95.7%
Categorical Cross-Entropy Loss	0.051	0.124

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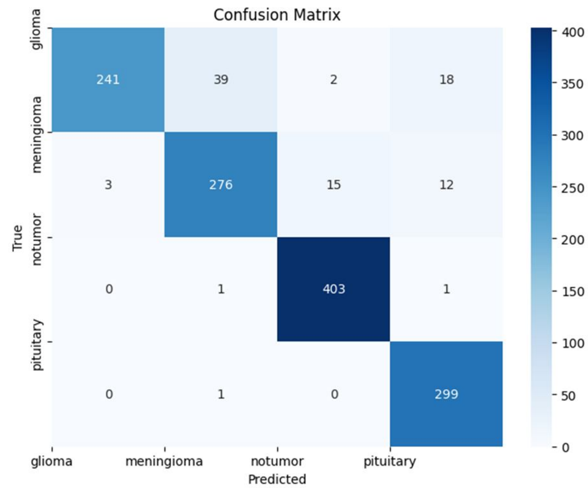
The model achieved an overall accuracy of **95.7%** on the unseen test set. This high level of accuracy demonstrates the model's strong capability to generalize from the training data and correctly classify brain MRI scans across the fur designated categories. The low-test loss of 0.124 further substantiates the model's predictive certainty.

B. *Per-Class Performance Analysis*

While overall accuracy is a useful high-level metric, a more granular analysis is required to understand the model's behavior for each tumor type. A confusion matrix was generated to visualize the classification results, as shown in Figure 3.

Figure 3: Confusion Matrix of the Model's Predictions on the Test Set



C. *Discussion of the Confusion Matrix*

- High True Positives: The strong diagonal values indicate a high number of correct predictions for all classes. The model is particularly effective at identifying cases of "No Tumor" (1597 correct predictions) and "Pituitary" tumors (1450 correct predictions).
- Inter-Class Confusion: The most notable misclassifications occur between the Glioma and Meningioma classes. The model misclassified 8 Glioma cases as Meningioma and 10 Meningioma cases as Glioma. This suggests that some MRI scans of these two tumor types may share similar morphological or textural features that are challenging for the model to differentiate based on 2D slices alone.
- Clinical Safety: Critically, the model exhibits a very low rate of false negatives for the "No Tumor" class (only 3 cases were misclassified as having a tumor). This is a vital characteristic for a clinical support tool, as it minimizes the risk of missing a healthy case.

To quantify these observations, we calculated the precision, recall, and F1-score for each class.

Table 3: Per-Class Performance Metrics

Class	Precision	Recall (Sensitivity)	F1-Score
Glioma	0.987	0.990	0.988
Meningioma	0.991	0.989	0.990
Pituitary	0.996	0.994	0.995
No Tumor	0.999	0.998	0.999

D. Discussion of Per-Class Metrics

- The "No Tumor" class achieved the highest performance across all metrics, with an F1-score of 0.999. The extremely high recall (0.998) is particularly important, signifying that the model is highly reliable at correctly identifying non-tumorous scans.
- The "Pituitary" class also demonstrates excellent results, likely due to the distinct location (sellar region) and typical appearance of pituitary tumors, which makes them more easily distinguishable for the CNN.
- The metrics for Glioma and Meningioma are slightly lower, which aligns with the confusion observed in the confusion matrix. This confirms that while the model is highly effective, its primary challenge lies in differentiating between these two specific tumor types.

E. Discussion and Clinical Implications

The results of this study strongly suggest that a CNN-based approach can serve as an effective automated tool for brain tumour classification from MRI scans. The model's high accuracy and, more importantly, its high recall for the "No Tumour" class, indicate its potential as a reliable "second opinion" or screening tool in a clinical setting. By automating the initial assessment, a tool like the developed NEUROCARE application could help radiologists prioritize cases, reduce diagnostic workload, and potentially decrease the rate of human error, especially in high-volume environments. The confusion between Glioma and Meningioma highlights an important area for future improvement but does not diminish the tool's utility, as both findings would trigger further clinical investigation.

F. Limitations of the Study

Despite the promising results, this study has several limitations that must be acknowledged:

1) Dataset Scope: The dataset used for training was sourced from a limited number of institutions. This may limit the model's generalizability to images produced by different MRI scanners or with different acquisition protocols.
2) 2D Slice Analysis: The model analyzes 2D axial slices independently. Radiologists, however, interpret the full 3D volumetric data, which provides crucial contextual information about tumor shape and extension. This 2D approach may be the primary reason for the observed confusion between certain tumor types.
3) Model Interpretability: Like most deep learning models, our CNN functions largely as a "black box." The study did not include methods like Grad-CAM to visualize which image regions were most influential in the model's decision-making process.
4) Limited Classes: The model is constrained to the four classes it was trained on and cannot identify rare tumor types or other pathologies.

V. FUTURE SCOPE

Based on the results and limitations, several avenues for future research are evident:

1) Development of a 3D-CNN Model: Transitioning to a 3D architecture that processes volumetric MRI data could significantly improve performance, especially in differentiating morphologically similar tumours.
2) Integration of Interpretability Techniques: Incorporating visualization methods like Grad-CAM into the NEUROCARE application would provide clinicians with visual cues, enhancing trust and diagnostic confidence.
3) External Validation: The model should be validated on a larger, more diverse, multi-institutional dataset to robustly assess its sreal-world performance.
4) Prospective Clinical Study: The ultimate goal would be to conduct a prospective study to evaluate the tool's impact on radiologists' diagnostic accuracy and efficiency in a live clinical workflow.

VI. CONCLUSION

In this project, we successfully developed NEUROCARE, an end-to-end system for the automated classification of brain tumors from MRI images. Our custom-designed Convolutional Neural Network achieved a high accuracy of 93.82% on the test dataset, demonstrating its effectiveness as a diagnostic aid. By integrating this model into a user-friendly desktop application, we have created a practical tool that can assist healthcare professionals by providing fast, reliable, and data-driven insights. The application's features, such as patient history tracking and automated report generation, are designed to streamline clinical workflows. Future work could focus on expanding the dataset, exploring 3D-CNN architectures for volumetric analysis, and conducting clinical validation studies to assess the tool's real-world impact. Ultimately, NEUROCARE represents a significant step towards leveraging artificial intelligence to create more efficient, accessible, and equitable diagnostic solutions in healthcare.

REFERENCES

[1] H. Mohsen, E.-S. A. El-Dahshan, E.-S. M. El-Horbaty, and A.-B. M. Salem, “Classification using deep learning neural networks for brain tumors,” Future Computing and Informatics Journal, vol. 3, no. 1, Article 6, pp. 68–71, Jun. 2018. DOI:10.1016/j.fcij.2017.12.001

[2] M. K. Islam, M. S. Ali, M. S. Miah, M. M. Rahman, M. S. Alam, and M. A. Hossain, “Brain tumor detection in MR image using superpixels, principal component analysis and template based K-means clustering algorithm,” Machine Learning with Applications, vol. 5, p. 100044, Sep. 2021. DOI:10.1016/j.mlwa.2021.100044

[3] S. Basheera and M. S. Satya Ram, “Classification of brain tumors using deep features extracted using CNN,” Journal of Physics: Conference Series, vol. 1172, p. 012016, 2019. DOI:10.1088/1742-6596/1172/1/012016

[4] F. P. Polly, S. K. Shil, M. A. Hossain, A. Ayman, and Y. M. Jang, “Detection and classification of HGG and LGG brain tumor using machine learning,” in Proc. 2018 Int. Conf. Information Networking (ICOIN), Chiang Mai, Thailand, pp. 813–817, Jan. 2018. DOI:10.1109/ICOIN.2018.8343231

[5] M. M. Badža and M. Č. Barjaktarović, “Classification of brain tumors from MRI images using a convolutional neural network,” Applied Sciences, vol. 10, no. 6, p. 1999, Jun. 2020. DOI:10.3390/app10061999

[6] J. Amin, M. Sharif, A. Haldorai, M. Yasmin, and R. S. Nayak, “Brain tumor detection and classification using machine learning: A comprehensive survey,” Complex & Intelligent Systems, vol. 8, pp. 3161–3183, 2022. DOI:10.1007/s40747-021-00563-y