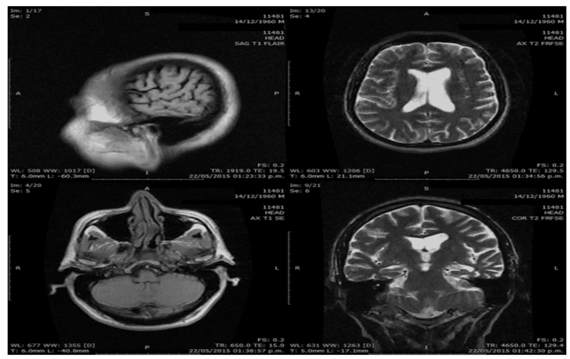
PROJECT REPORT

Topic: Brain Tumor Classification using OpenCV and Convolutional Neural Networks (CNN)



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Preface

This report presents my end-to-end project on Brain Tumor Classification using OpenCV and Convolutional Neural Networks (CNN), completed as part of my Advanced Machine Learning coursework during my MS in Data Science at UMass Dartmouth. The primary motivation behind this project was to explore how deep learning and computer vision techniques can be applied to real-world healthcare problems, particularly in medical image analysis using MRI scans.

Unlike traditional machine learning projects that focus on structured tabular data, this project involves complex medical image data, which requires specialized preprocessing, visual analysis, and deep learning-based feature extraction. Through this work, I aimed to build not just a model, but a complete AI pipeline --- starting from raw image loading and preprocessing with OpenCV, to CNN model development, training, evaluation using professional metrics, and real-world prediction analysis.

This report is designed to be both technical and beginner-friendly. It systematically guides the reader through the full workflow, including the theoretical background of brain tumors, dataset structure, image preprocessing logic, CNN architecture design, and performance evaluation using confusion matrix, precision, recall, and F1-score. Special emphasis is given to explaining the reasoning behind each step, so that even readers who are new to medical AI and computer vision can clearly understand the methodology and results.

Additionally, this project reflects my practical learning in applied deep learning, medical imaging, and model evaluation in sensitive domains like healthcare, where reliability and interpretability are as important as accuracy. By the end of this report, the reader will gain a clear understanding of how AI can assist in automated tumor classification, the challenges involved in medical image analysis, and the real-world significance of such systems in supporting clinical decision-making.

Overall, this report serves as a comprehensive documentation of my hands-on experience in building a real-world medical AI solution, combining theoretical understanding, practical implementation, and critical performance analysis in a structured and professional manner.

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1. Introduction

In this project, I worked on a real-world medical AI problem: automatic brain tumor classification using MRI images. The main goal was to build an end-to-end deep learning pipeline that can process medical image data, learn meaningful visual patterns, and accurately classify different types of brain tumors.

Unlike traditional tabular machine learning projects, this project focuses on image data, which is more complex and closer to real-world AI applications in healthcare. I implemented the full workflow including data preprocessing using OpenCV, exploratory analysis of image data, CNN model training, and professional evaluation using confusion matrix and classification metrics.

This project was completed as part of my Advanced Machine Learning coursework, where the focus was on applying deep learning concepts to real-world datasets and understanding both theoretical and practical aspects of model development.

2. Problem Statement

Brain tumors are abnormal growths of cells inside the brain, and early detection is extremely important for medical diagnosis and treatment planning. Manual analysis of MRI scans by radiologists is time-consuming and requires high expertise.

The objective of this project is:

To develop an AI-based image classification model that can automatically identify the type of brain tumor from MRI images.

This is a multi-class classification problem where the model must classify MRI scans into four categories:

- Glioma Tumor
- Meningioma Tumor
- Pituitary Tumor
- No Tumor (Healthy Brain)

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3. Dataset Description

3.1 Dataset Source

The dataset used in this project is a publicly available Brain Tumor MRI dataset from Kaggle. It contains labeled MRI brain scans categorized into different tumor types and healthy cases.

3.2 Dataset Structure

The dataset is organized into folder-based image classes:

- Training/
  - glioma
  - meningioma
  - pituitary
  - notumor
- Testing/
  - glioma
  - meningioma
  - pituitary
  - notumor

3.3 Dataset Size

- Training Images: 5600
- Testing Images: 1600
- Total Classes: 4
- Images per class: ~1400 (balanced dataset)

Having a balanced dataset is important because it prevents model bias toward any single class.

4. Understanding Brain Tumor Categories (Theory)

4.1 What is a Brain Tumor?

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A brain tumor is an abnormal mass of tissue in the brain where cells grow uncontrollably. These tumors can affect brain function and can be life-threatening if not detected early.

4.2 Types of Tumors in This Dataset

1. Glioma

Gliomas are tumors that originate in the brain's glial cells. They are often aggressive and visually complex in MRI scans, which makes them harder for AI models to classify correctly.

2. Meningioma

Meningiomas develop in the meninges (protective layers of the brain). They usually appear as well-defined masses in MRI images.

3. Pituitary Tumor

These tumors occur in the pituitary gland and are relatively distinct in MRI structure, which explains why models often classify them with high accuracy.

4. No Tumor

This class contains healthy brain MRI scans and serves as a baseline for distinguishing between normal and abnormal medical images.

5. Methodology Overview

The project follows a complete deep learning pipeline:

1. Data Loading from image folders
2. Image Preprocessing using OpenCV
3. Exploratory Data Analysis (EDA for images)
4. Data Reshaping for CNN input
5. CNN Model Architecture Design
6. Model Training and Validation
7. Model Evaluation using professional metrics
8. Sample Prediction Visualization

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6. Image Preprocessing using OpenCV

Since MRI images are raw medical scans, preprocessing is essential before feeding them into a neural network.

6.1 Why Convert to Grayscale?

MRI scans are inherently grayscale medical images. Converting RGB images to grayscale:

- Reduces computational complexity
- Focuses on structural patterns instead of color
- Makes the model learn medically relevant features

This converts the image from 3 channels (RGB) to 1 channel.

6.2 What is Denoising and Why It Matters?

Medical images often contain noise due to scanning conditions. I applied Gaussian Blur to:

- Reduce random pixel noise
- Smooth image texture
- Improve feature extraction for CNN

6.3 Image Normalization

Pixel values were normalized from 0–255 to 0–1 range:

- Helps faster model convergence
- Stabilizes gradient learning
- Standard practice in deep learning

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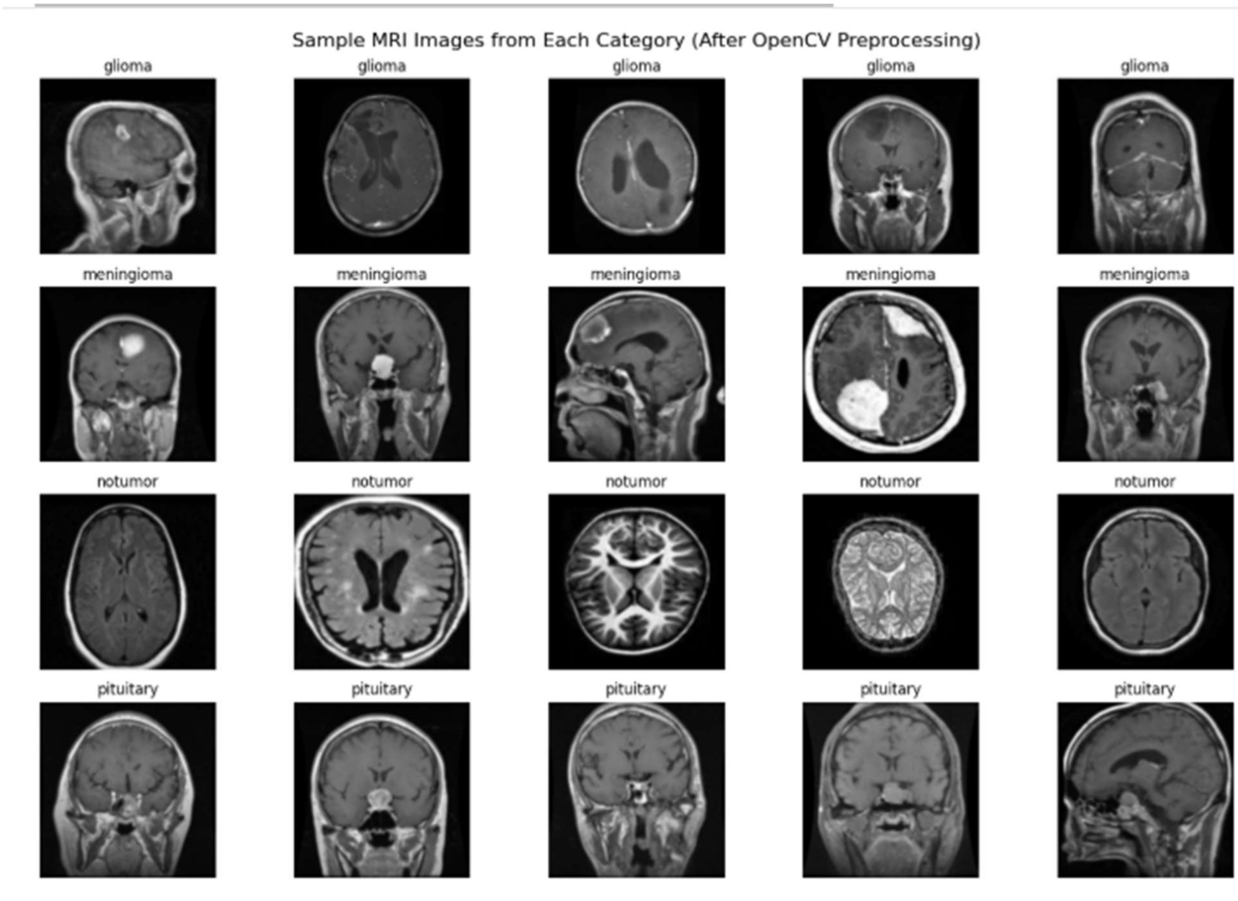

7. Exploratory Data Analysis (EDA for Image Data)

Unlike tabular datasets, image EDA involves:

- Visual inspection of sample MRI images
- Pixel distribution analysis
- Class balance verification
- Checking preprocessing outputs

Key Observations:

- Pixel Mean ≈ 0.18 - Dark medical background (normal for MRI)
- Pixel Std Dev ≈ 0.18 - Moderate variation (good contrast)
- Images are medically consistent after preprocessing

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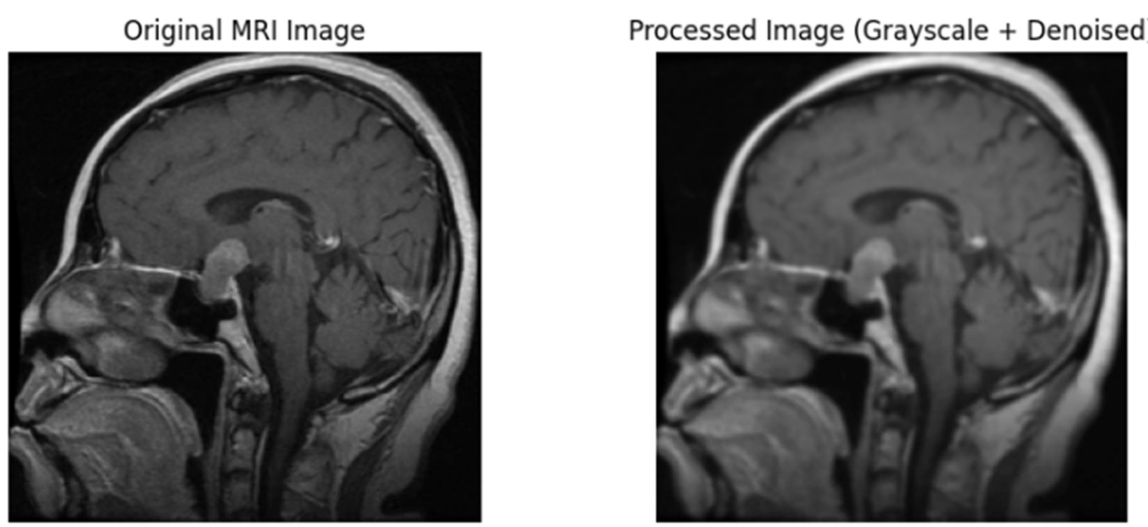
This confirmed that the dataset was clean and suitable for deep learning.



8. CNN Model Architecture

8.1 Why CNN Instead of Traditional ML?

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Traditional ML (like SVM or Random Forest) cannot automatically extract visual features. CNNs are specifically designed for image learning because they:

- Detect edges
- Capture spatial patterns
- Learn hierarchical visual features

8.2 Model Design Logic

The CNN architecture used multiple convolution blocks:

- Conv2D Layers → Feature extraction (tumor patterns)
- Batch Normalization → Stable training
- MaxPooling → Dimensionality reduction
- Dense Layers → Final classification decision
- Dropout → Prevent overfitting (important in medical AI)

The final output layer used Softmax activation for 4-class classification.

9. Model Training Details

- Epochs: 15 (interrupted at ~10 due to time)
- Batch Size: 32
- Optimizer: Adam (learning_rate = 0.0001)
- Loss Function: Categorical Crossentropy
- Input Shape: (224, 224, 1)

Training was computationally intensive due to:

- High-resolution medical images
- Deep CNN architecture
- Large dataset size (5600 images)

10. Model Performance Evaluation

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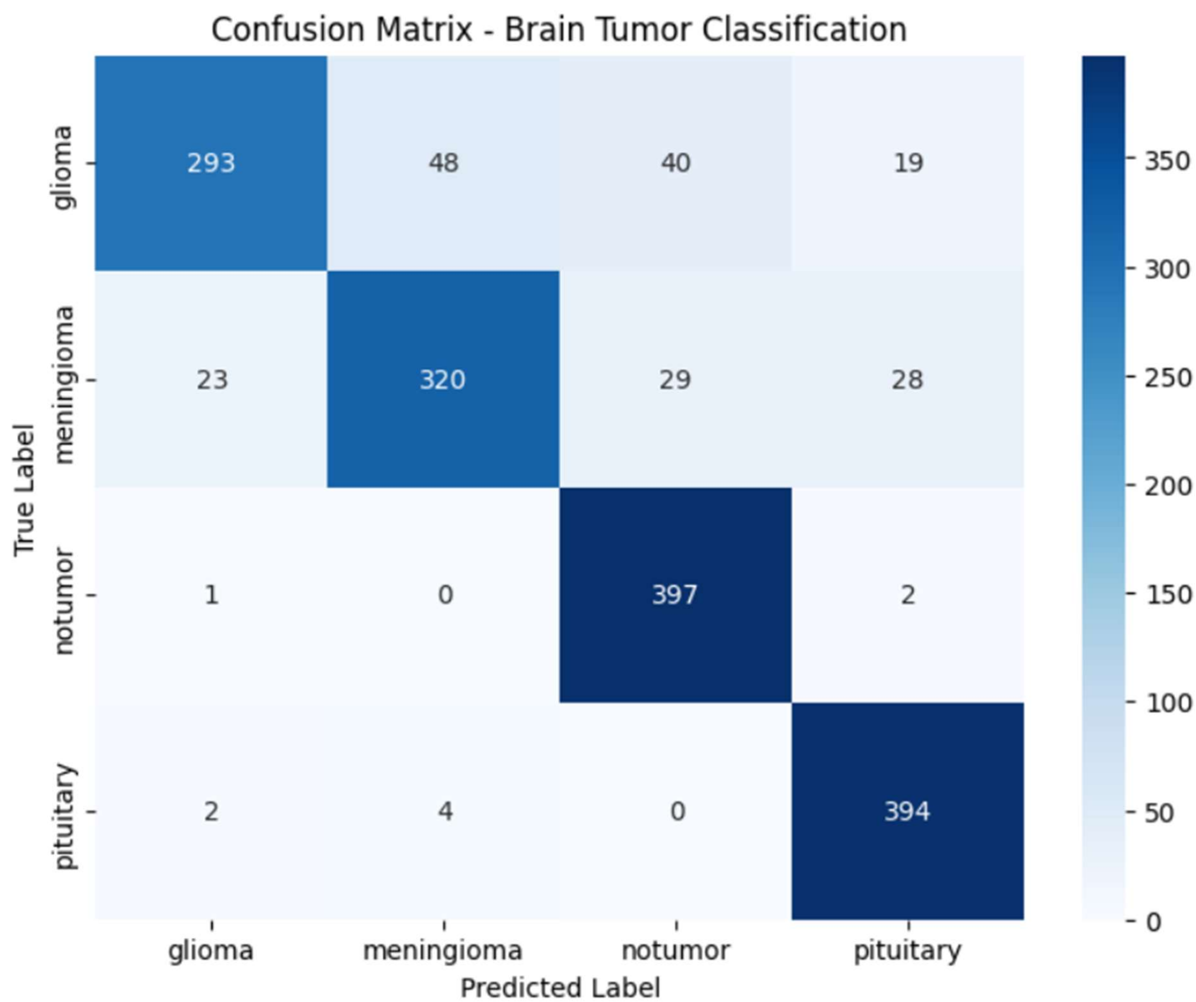
10.1 Final Test Accuracy

Test Accuracy: **87.75%**

The model correctly classifies approximately 88 out of 100 unseen MRI scans. It's a strong performance for a custom CNN trained from scratch.

10.2 Confusion Matrix Analysis (Medical Perspective)



Key Findings:

- Notumor: 397/400 correctly classified (Excellent)
- Pituitary: 394/400 correctly classified (Very High Accuracy)
- Meningioma: Good performance with minor confusion
- Glioma: Some confusion with other tumor types (expected due to visual similarity)

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This behavior is realistic because tumor textures often overlap in MRI scans.

10.3 Classification Report Interpretation

Overall Metrics:

- Precision: ~0.88
- Recall: ~0.88
- F1-Score: ~0.87

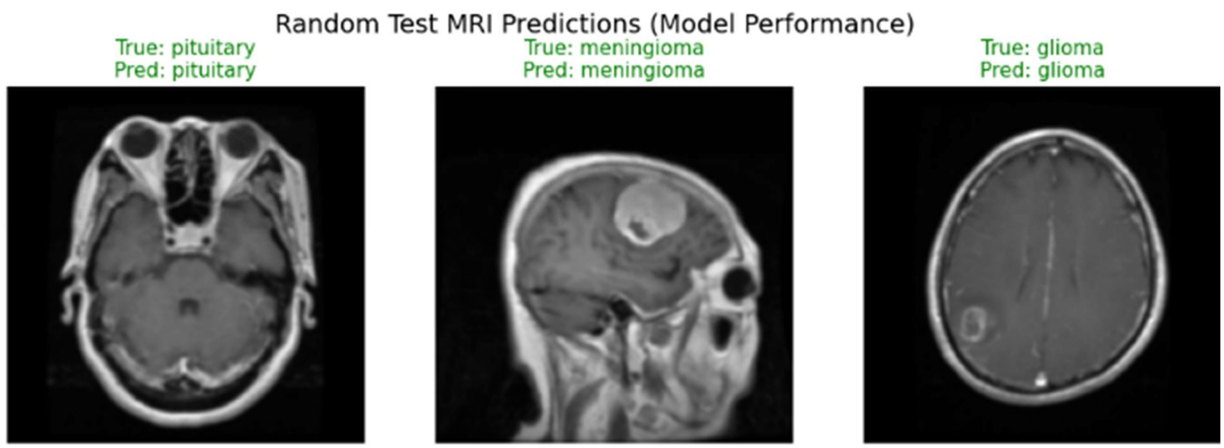
Medical Insight: High recall for tumor classes is especially important because missing a tumor is more critical than a false positive.

11. Sample Predictions (Real-World Validation)

Random test MRI images were passed through the trained model, and the model successfully predicted:

- Glioma
- Meningioma
- Pituitary tumors

The predictions matched true labels in most cases, demonstrating strong generalization ability on unseen medical data.



12. Key Achievements of This Project

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- Built a full end-to-end medical AI pipeline
- Applied OpenCV for medical image preprocessing
- Implemented CNN from scratch (no pretrained model)
- Achieved ~88% accuracy on real MRI dataset
- Performed professional evaluation (Confusion Matrix + Classification Report)
- Gained hands-on experience in medical image analysis

13. Limitations of the Model

- Training time was high due to large image size (224×224)
- Some confusion between similar tumor types (glioma vs meningioma)
- Model trained from scratch instead of transfer learning (could improve accuracy)

14. Future Improvements

- Use Transfer Learning (ResNet, EfficientNet) for higher accuracy (90–95%)
- Apply data augmentation for better generalization
- Use segmentation models for tumor localization
- Optimize training using GPU acceleration

15. Conclusion

In this project, I developed a complete deep learning pipeline for brain tumor classification using OpenCV-based preprocessing and a custom CNN model trained on real MRI images. The model achieved a test accuracy of 87.75% on unseen data, with particularly strong performance in identifying healthy scans and pituitary tumors, while maintaining balanced classification across all four categories. These results show that a well-designed CNN, combined with proper preprocessing and careful evaluation, can effectively learn meaningful patterns from complex medical imaging data.

Beyond the final accuracy, the most valuable takeaway from this work was gaining a deeper practical understanding of how theoretical concepts in computer vision, deep learning,

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and model evaluation apply to real-world healthcare problems. Working with MRI images, interpreting confusion matrices, and analyzing class-wise performance helped me appreciate the importance of reliability and thoughtful model assessment in sensitive domains like medical AI. Overall, this project reflects a meaningful application of advanced machine learning to a real and impactful problem, and it has strengthened both my technical foundation and my motivation to further explore AI solutions in healthcare and real-world decision-support systems.

References

1. Nickparvar, M. (2023). *Brain Tumor MRI Dataset*. Kaggle. https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset
2. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436–444.
   (Foundational paper explaining deep learning and neural networks)
3. Krizhevsky, A., Sutskever, I., & Hinton, G. (2012). ImageNet classification with deep convolutional neural networks. *Advances in Neural Information Processing Systems (NeurIPS)*.
   (Classic CNN paper used as theoretical foundation)
4. Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT Press.
   (Standard textbook for CNN and deep learning theory)
5. OpenCV Library Documentation. (2024). Open Source Computer Vision Library. https://docs.opencv.org/
   (Used for image preprocessing, grayscale conversion, and denoising)
6. Chollet, F. (2023). *Deep Learning with Python (2nd Edition)*. Manning Publications.
   (Keras and CNN implementation reference)
7. TensorFlow Keras Documentation. (2024). https://www.tensorflow.org/api_docs/python/tf/keras
   (Used for CNN model building, training, and evaluation)
8. Litjens, G., et al. (2017). A survey on deep learning in medical image analysis. *Medical Image Analysis*, 42, 60–88.
   (Very strong medical AI reference – interview gold)

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9. Han, X. (2020). MR-based brain tumor classification using deep learning methods: A review. *Frontiers in Oncology*, 10, 594445.
(Directly related to brain tumor classification)

10. Scikit-learn Documentation. (2024).
https://scikit-learn.org/stable/
(Used for confusion matrix, classification report, and evaluation metrics)

Thank you,

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