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BRAIN TUMOR DETECTION USING DEEP LEARNING

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ABSTRACT

The proposed project aims to develop an intelligent Brain Tumor Detection System using advanced deep learning techniques to address critical challenges in medical image analysis. The system analyzes MRI brain scan images and classifies them into four categories: Glioma, Meningioma, No Tumor, and Pituitary Tumor. By automating image classification, the project seeks to support healthcare professionals in making faster and more consistent assessments. The core component of the system is a custom Convolutional Neural Network (CNN) architecture, BrainTumorCNN_v2. The model consists of four convolutional blocks with filters ranging from 32 to 256, along with Batch Normalization and Dropout layers to improve learning stability and reduce overfitting. Global Average Pooling is incorporated to efficiently extract high-level image features. The model is trained using 150×150 pixel MRI images representing the four target classes. To improve model generalization and robustness, the system incorporates a comprehensive data augmentation pipeline. Random flipping, rotation, zooming, translation, and contrast adjustment are applied to training images, helping the model learn meaningful features despite variations in MRI image appearance and limited medical datasets. A modular Python-based prediction interface is also included. It accepts MRI images as input, loads the trained CNN model, processes the image, and generates predicted class probabilities. These outputs can provide valuable decision-support information for radiologists, clinicians, and healthcare stakeholders. Overall, the proposed system demonstrates the potential of deep learning and medical image analysis to assist brain tumor classification, improve diagnostic efficiency, and support data-driven healthcare. However, it is intended as a clinical decision-support tool rather than a replacement for professional medical diagnosis.

Keywords: *Brain tumor detection, MRI classification, deep learning, CNN, medical image analysis, Glioma, Meningioma, Pituitary Tumor, TensorFlow, Keras, data augmentation, healthcare AI, classification.*

I. INTRODUCTION

1.1 Background

Medical imaging plays a pivotal role in modern healthcare, particularly in the diagnosis of neurological disorders such as brain tumors. Brain tumors are abnormal growths of cells within the brain and may be classified into different types based on their origin and characteristics. Early and accurate detection is critical for determining appropriate treatment strategies and improving patient outcomes [1], [3].

Magnetic Resonance Imaging (MRI) is widely used for brain tumor visualization because of its excellent soft-tissue contrast and non-ionizing nature. However, manual interpretation of MRI scans is time-consuming and can be affected by inter-observer variability and the experience of the radiologist [11], [14]. With the increasing volume of medical imaging data, automated and reliable diagnostic-support systems have become increasingly important.

The development of **Deep Learning and Convolutional Neural Networks (CNNs)** has significantly improved computer-aided medical image analysis. CNNs can automatically learn hierarchical spatial features directly from images, making them highly suitable for image classification tasks [3], [4], [13]. Transfer learning and deep CNN-based approaches have also demonstrated promising results in brain tumor classification [4], [17], [23].

This project utilizes these capabilities to develop an end-to-end brain tumor classification pipeline using MRI images.

Current Challenges in Brain Tumor Diagnosis

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- **Manual Review Burden:** Radiologists must examine large numbers of MRI images, making the process time-consuming and potentially increasing workload-related errors [11], [13].
- **Class Ambiguity:** Different brain tumor types may exhibit similar visual characteristics, making accurate classification challenging [3], [18].
- **Data Scarcity:** Medical imaging datasets with reliable expert annotations are limited because of privacy, availability, and annotation costs [5].
- **Generalization:** Differences in imaging equipment, acquisition protocols, and patient populations can affect the generalization of deep learning models [18], [19].

1.2 Problem Statement

Despite significant advances in medical AI, brain tumor diagnosis still depends heavily on expert interpretation of MRI images. Existing approaches face challenges related to classification accuracy, limited datasets, model generalization, and reliable prediction outputs [18], [19].

The major problems addressed by this project are:

1. **Diagnostic Delays:** Manual MRI analysis can be time-consuming in high-volume clinical environments [11].
2. **Classification Errors:** Differentiating between multiple tumor categories remains challenging because of similarities in MRI characteristics [3], [17].
3. **Lack of Probability Outputs:** Classification systems can be improved by providing confidence or probability scores for individual classes, supporting more informative decision-making [20].
4. **Computational Limitations:** Highly complex deep learning architectures may require significant computational resources, creating challenges for practical deployment [21], [24].

1.3 Objectives

The main objectives of this project are:

1. To design and train a custom CNN model, **BrainTumorCNN_v2**, for classifying MRI brain scans into four categories: **Glioma, Meningioma, No Tumor, and Pituitary Tumor** [3], [17].
2. To implement data augmentation and regularization techniques to improve model generalization and reduce overfitting [1], [5].
3. To achieve reliable classification performance across all four tumor categories.
4. To develop a modular prediction interface that provides predicted classes along with probability scores.
5. To evaluate the model using **Accuracy, Precision, Recall, F1-Score, and Confusion Matrix** metrics [3], [19].

1.4 Scope

The project focuses on multi-class MRI classification using a publicly available brain tumor dataset [9]. The system covers the complete machine-learning workflow, including **data loading, preprocessing, augmentation, CNN model development, training, evaluation, and inference**.

The trained model can be saved in Keras format and used through a Python-based prediction script without requiring complete retraining. TensorFlow/Keras provides suitable tools for image dataset loading, preprocessing, model development, and deployment [6], [8].

The project is primarily intended for **academic research and clinical decision-support research**, rather than independent medical diagnosis.

1.5 Significance of the Project

The proposed system demonstrates the potential of deep learning for automated brain tumor classification from MRI images. Such systems can assist healthcare professionals by providing rapid preliminary classification and reducing repetitive image-analysis workload [3], [4].

The project also provides an educational and research foundation for implementing medical image classification using TensorFlow and Keras. Its

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evaluation framework can be extended to other medical imaging applications and advanced explainable-AI techniques such as **Grad-CAM**, which can help visualize image regions influencing CNN predictions [10].

II. LITERATURE REVIEW

In recent years, numerous research studies have explored the application of **Deep Learning**, particularly **Convolutional Neural Networks (CNNs)**, in medical image analysis. CNN-based approaches have demonstrated strong potential for automatically extracting meaningful features from MRI images and classifying different types of brain tumors [3], [4], [13], [19]. This section highlights key studies relevant to brain tumor classification and their contributions to the proposed project.

2.1 Previous Work

2.1.1 CNN-Based Medical Image Classification

Cheng et al. introduced a brain tumor classification approach based on MRI images and demonstrated the effectiveness of image-processing and machine-learning techniques for distinguishing different tumor categories [1]. Their work established an important foundation for automated brain tumor classification using medical images.

Afshar et al. proposed a **Capsule Network** architecture for brain tumor classification. Their approach attempted to preserve spatial relationships between image features and demonstrated the potential of capsule-based architectures for medical image classification [2]. However, such architectures can require greater computational complexity compared with conventional CNN models.

Sultan et al. developed a deep neural network approach for multi-class brain tumor classification and demonstrated the effectiveness of deep learning for distinguishing different tumor types from MRI images [3]. Their research supports the use of CNN-based approaches for automated multi-class brain tumor classification.

2.1.2 Transfer Learning in Brain Tumor Detection

Deepak and Ameer investigated brain tumor classification using deep CNN features and **transfer learning**. Their study demonstrated that features extracted from pre-trained deep learning networks can provide effective representations for MRI-based tumor classification [4].

Transfer learning has subsequently become an important technique in medical image analysis because pre-trained models can reduce training requirements when medical datasets are relatively small [17], [23]. Recent research has also investigated ResNet, EfficientNet, and other pre-trained architectures for improving brain tumor classification performance [21]–[24].

2.1.3 Data Augmentation for Medical Imaging

Hussain et al. studied different data augmentation techniques for medical image classification and demonstrated that augmentation can improve the robustness and generalization of deep learning models [5]. Techniques such as rotation, flipping, zooming, and other image transformations can increase training-data variability and help reduce overfitting.

Data augmentation is particularly important for medical imaging because obtaining large, accurately annotated datasets is challenging due to privacy requirements, expert-annotation costs, and limited availability of high-quality datasets [5], [18], [19].

2.2 Gaps in Existing Solutions

Despite significant progress, several limitations remain in existing brain tumor classification systems:

1. **Class Imbalance and Per-Class Performance:** Many studies emphasize overall accuracy, while detailed analysis of Precision, Recall, and F1-Score for individual tumor classes is also important [3], [19].
2. **Lack of Modular Inference:** Many research studies primarily focus on model development and experimental results. A standalone prediction pipeline can make the trained model easier to test and reuse.
3. **Computational Requirements:** Large transfer-learning architectures can provide strong performance but may require

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considerable computational resources. Recent research has therefore investigated lightweight and efficient architectures [21], [22], [25].

4. **Limited Explainability:** CNN models can operate as complex black-box systems. Explainable-AI techniques such as **Grad-CAM** can help visualize the image regions contributing to model predictions [10].

2.3 How This Project Addresses the Gaps

2.3.1 Custom CNN Architecture

Instead of relying entirely on large pre-trained architectures, this project develops a purpose-built **BrainTumorCNN_v2** architecture consisting of four progressively deeper convolutional blocks. The approach is designed to provide an effective balance between classification capability and computational efficiency, building upon the established effectiveness of CNNs for brain tumor classification [1], [3], [4].

2.3.2 Per-Class Evaluation Framework

The proposed evaluation framework reports **Accuracy, Precision, Recall, F1-Score, and Confusion Matrix** results. This provides a more comprehensive assessment of model performance across the four target classes rather than relying only on overall accuracy [3], [19].

2.3.3 Modular Prediction Pipeline

A standalone **predict.py** inference script is included to load the trained Keras model, process an MRI image, and generate the predicted tumor class along with probability scores. This provides a practical extension from experimental model development toward reusable inference.

2.3.4 Regularization and Augmentation Strategy

The proposed model incorporates **Dropout, L2 regularization, Label Smoothing, and data augmentation** to reduce overfitting and improve generalization. These techniques are consistent with established deep-learning practices and research on augmentation for medical image classification [5]-[7].

III. PROPOSED SYSTEM

PROPOSED SYSTEM MODULES

3.1 Dataset Collection Module

This module collects MRI brain images from the selected publicly available dataset. The images are organized into four categories: **Glioma, Meningioma, No Tumor, and Pituitary Tumor**. The dataset is divided into training and testing sets for model development and evaluation.

3.2 Data Preprocessing Module

The collected MRI images are preprocessed before being provided to the CNN model. Images are resized to **150 × 150 pixels**, normalized, and converted into a suitable format for TensorFlow/Keras processing.

3.3 Data Augmentation Module

To improve model generalization and reduce overfitting, various augmentation techniques are applied, including **random flipping, rotation, zooming, translation, and contrast adjustment**.

3.4 CNN Model Development Module

This is the core module of the system. The proposed **BrainTumorCNN_v2** consists of four convolutional blocks with progressively increasing filters from **32 to 256**. Batch Normalization, Dropout, and Global Average Pooling are used to improve learning and reduce overfitting.

3.5 Model Training Module

The preprocessed and augmented MRI images are used to train the CNN model. The model learns important visual features associated with different tumor categories and stores the trained parameters in a **.keras model file**.

3.6 Model Evaluation Module

The trained model is evaluated using standard classification metrics, including **Accuracy, Precision, Recall, F1-Score, and Confusion Matrix**. These metrics help determine the performance of the model for each tumor category.

3.7 Prediction Module

The prediction module provides a standalone **Python predict.py interface**. It accepts an

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MRI image as input, loads the trained model, processes the image, and predicts one of the four tumor classes along with its probability score.

3.8 Result Visualization Module

This module displays prediction results and evaluation outputs such as **classification reports, confusion matrices, accuracy graphs, and probability scores**, making the model performance easier to understand.

3.9 Explainable AI Module

An optional **Grad-CAM** component can be incorporated to highlight the regions of an MRI image that influenced the CNN's prediction. This improves model interpretability and can provide useful visual decision-support information.

3.10 Dataset Description

The **Brain Tumor Detection System** uses a publicly available **Brain Tumor MRI Dataset** containing brain MRI images categorized into four classes: **Glioma, Meningioma, No Tumor, and Pituitary Tumor**. The dataset is used to train and evaluate the Convolutional Neural Network (CNN) model for automatic multi-class brain tumor classification.

The dataset contains **5,712 training images and 1,311 testing images**. Before being provided to the CNN, all MRI images are resized to **150 × 150 pixels** and normalized to ensure consistent input dimensions and pixel values.

To improve model generalization and reduce overfitting, data augmentation techniques such as **random flipping, rotation, zooming, translation, and contrast adjustment** are applied to the training images.

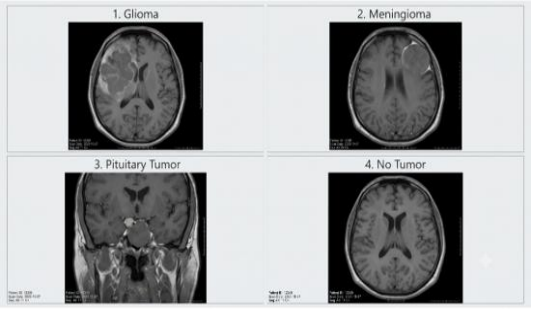


Figure 4.1: Four-Class MRI Dataset Categories (Glioma, Meningioma, Pituitary, and No Tumor)

- **Data Augmentation Transformations** (Illustrating rotation, horizontal flipping, zooming, and contrast variations used to improve model generalization):

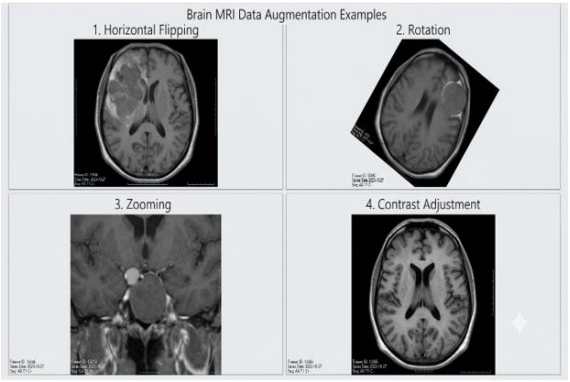


Figure 4.2: Data Augmentation Transformations

IV. SYSTEM ARCHITECTURE AND WORKFLOW

The **Brain Tumor Detection System** is designed as a deep learning-based medical image classification system. It accepts brain MRI images as input, preprocesses and augments the images, trains a Convolutional Neural Network (CNN), evaluates its performance, and predicts the tumor category with a probability score.

System Architecture

The architecture consists of the following major components:

MRI Dataset → Preprocessing → Data Augmentation → CNN Model → Training → Evaluation → Prediction → Result Visualization → Explainable AI

4.1. MRI Dataset

The system uses MRI brain images belonging

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to four classes:

- Glioma
- Meningioma
- No Tumor
- Pituitary Tumor

4.2. Preprocessing

The input MRI images are:

- Resized to **150 × 150 pixels**
- Converted into a suitable image format
- Normalized for consistent pixel values

4.3. Data Augmentation

To improve model generalization and reduce overfitting, the training images are augmented using:

- Random flipping
- Rotation
- Zoom
- Translation
- Contrast adjustment

4.4. CNN Model

The proposed **BrainTumorCNN_v2** consists of four convolutional blocks with increasing filters from **32 to 256**. Batch Normalization, Dropout, and Global Average Pooling are used to improve learning and regularization.

4.5. Model Training

The processed images are provided to the CNN for training. The model learns important visual patterns and features associated with different brain tumor categories.

4.6. Model Evaluation

The trained model is evaluated using:

- Accuracy
- Precision
- Recall
- F1-Score
- Confusion Matrix

4.7. Prediction

The predict.py module loads the trained .keras model and accepts a new MRI image. It predicts the tumor category and provides the corresponding probability score.

4.8. Result Visualization

The system displays prediction results, probability scores, performance graphs, and the confusion matrix for analysis.

4.9. Explainable AI

An optional **Grad-CAM** module can generate a heatmap showing the regions of the MRI image that influenced the CNN's prediction.

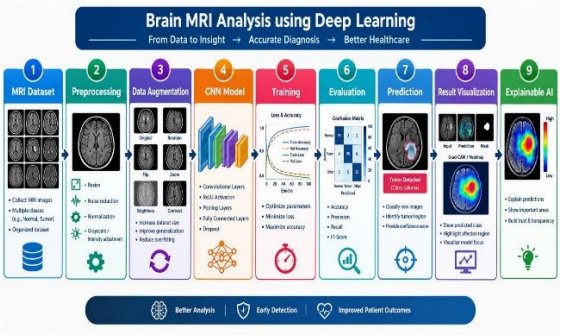


Figure 4.1: Architecture of Brain_Tumor_Detection using Deep Learning

V. METHODOLOGY

METHODOLOGY APPROACH

The methodology adopted for the **Brain Tumor Detection System** follows a systematic deep learning pipeline, beginning with MRI image collection and preparation and ending with model evaluation and prediction. The complete methodology is designed to provide reliable multi-class classification of brain MRI images into **Glioma, Meningioma, No Tumor, and Pituitary Tumor** categories.

5.1 Data Collection and Organization

MRI brain scan images are obtained from the publicly available **Kaggle Brain Tumor MRI Dataset**. The dataset is organized into separate **training and testing directories**, with each directory containing four class-labelled subdirectories: Glioma, Meningioma, No Tumor, and Pituitary Tumor. This folder-based organization allows TensorFlow/Keras to automatically identify class labels during dataset loading.

The dataset contains **5,712 training images and 1,311 testing images**. The testing data is kept separate from the training process to provide an unbiased assessment of the trained model.

5.2 Data Preprocessing

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MRI images may have different resolutions and pixel-value distributions. Therefore, preprocessing is performed before the images are supplied to the CNN. Each image is resized to **150 × 150 pixels** to maintain a consistent input dimension.

Pixel values are normalized to the **[0,1] range** using Rescaling(1/255). This normalization helps provide stable numerical values during neural network training and can contribute to faster and more consistent convergence.

5.3 Data Augmentation

Data augmentation is applied **only to the training dataset** to increase image variability and reduce overfitting. The augmentation pipeline includes:

- Random horizontal flipping
- Random rotation of approximately ±15%
- Random zoom of approximately ±15%
- Random translation of approximately 10%
- Random contrast adjustment of approximately 15%

The testing dataset is not augmented so that evaluation represents the model's performance on the original held-out images.

5.4 Model Architecture Design

A custom CNN architecture named **BrainTumorCNN_v2** is developed specifically for the classification task. The architecture consists of **four progressively deeper convolutional blocks**, allowing the network to learn increasingly complex visual features from MRI images.

The number of filters increases progressively from **32 to 256**. Batch Normalization is incorporated to stabilize the learning process, while Dropout is used to reduce overfitting. **Global Average Pooling** is used to reduce the dimensionality of extracted feature maps before the final classification layers.

The final output layer contains **four neurons**, corresponding to the four tumor categories, and uses Softmax activation to generate class probabilities.

5.5 Training Strategy

The CNN is trained using the **Adam optimizer** with an initial learning rate of $\mathbf{3 \times 10^{-4}}$. Categorical Cross-Entropy is used as the primary classification loss function, with **label smoothing of 0.1** to reduce excessive confidence in predictions and improve generalization.

Three important training callbacks are used:

- **Model Checkpoint:** Saves the best-performing model during training.
- **Early Stopping:** Stops training when validation performance does not improve for 12 consecutive epochs.
- **ReduceLROnPlateau:** Reduces the learning rate by a factor of 0.5 when validation performance stops improving for 4 epochs.

These techniques help prevent unnecessary training and reduce the risk of overfitting.

5.6 Regularization

Regularization techniques are incorporated into the model to improve generalization. **L2 weight regularization** discourages excessively large model weights, while progressive Dropout rates help prevent the network from becoming overly dependent on particular neurons or features.

The combination of data augmentation, Dropout, L2 regularization, and label smoothing provides multiple mechanisms for controlling overfitting.

5.7 Model Validation and Evaluation

After training, the **best saved model** is reloaded and evaluated using the independent test dataset. Multiple performance metrics are considered instead of relying only on overall accuracy.

The evaluation includes:

- **Accuracy** – measures overall correct classification.
- **Precision** – measures the proportion of positive predictions that are correct.
- **Recall** – measures the ability to identify samples belonging to a particular class.
- **F1-Score** – provides a combined measure of precision and recall.
- **Confusion Matrix** – shows the number of correct and incorrect predictions for each tumor category.

Per-class evaluation is particularly important because a high overall accuracy may not necessarily indicate balanced performance across all four

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classes.

5.8 Visualization of Results

Training and evaluation results are visualized using **Matplotlib** and other appropriate tools. Training and validation accuracy and loss curves are generated to observe the learning behavior of the model.

A **confusion matrix heatmap** is generated to identify which tumor categories are being correctly classified and which categories are frequently confused with one another. A classification report provides detailed precision, recall, and F1-score values for each class.

5.9 Prediction Module

A separate Python module, **predict.py**, is used for inference on new MRI images. The trained .keras model is loaded, and the input image undergoes the same basic preprocessing used during training.

The prediction pipeline follows:

Input MRI → Resize → Normalize → CNN Model → Softmax Prediction → Class Probability

The system returns the predicted tumor category along with probability scores for all four classes.

5.10 Explainable AI

As an optional enhancement, **Grad-CAM (Gradient-weighted Class Activation Mapping)** can be used to generate visual heatmaps. These heatmaps indicate regions of the MRI image that contributed strongly to the CNN's prediction.

This provides an additional layer of interpretability and can help researchers examine whether the model is focusing on meaningful image regions rather than irrelevant background patterns.

VI. SCREEN SHOTS

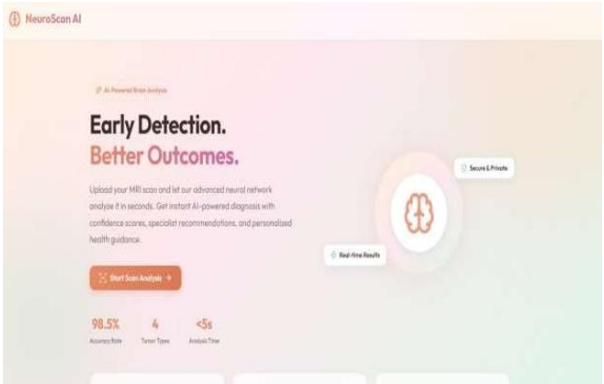


Figure 6.1 : Main Screen - Brain Tumor Detection front page

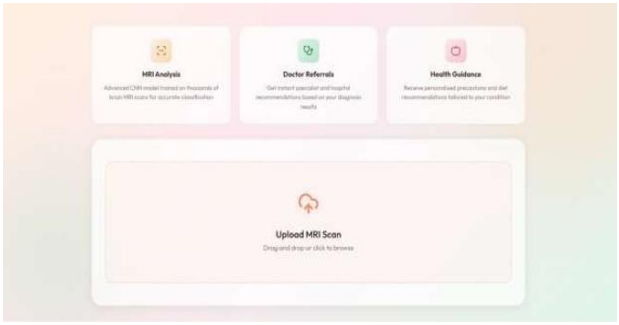


Figure 6.2 : Uploading MRI Image Screen – Brain Tumor Detection

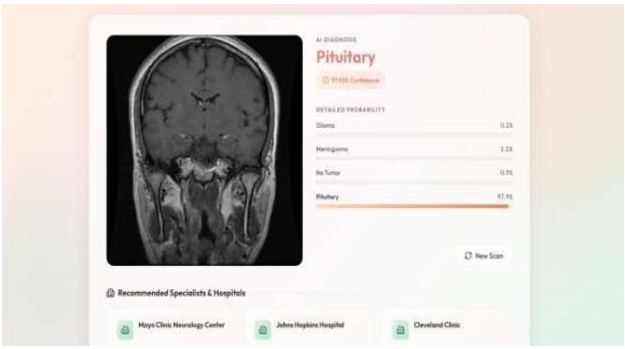


Figure 6.3 : Output MRI Scanned Image Screen - Brain Tumor Detection7

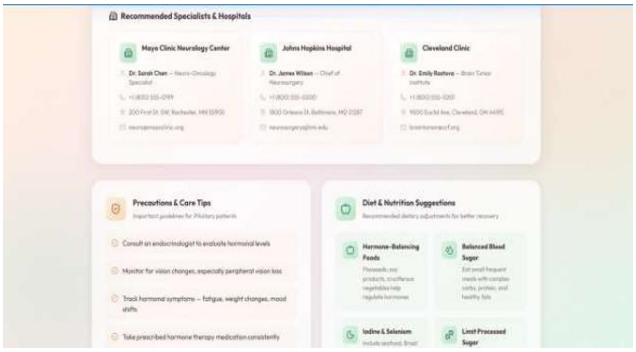


Figure 6.4 : Recommendations of Tumor treatment - Brain Tumor Detection

VII. CONCLUSION

Key Learnings

The Brain Tumor Detection System successfully developed and evaluated a custom Convolutional Neural Network (BrainTumorCNN_v2) for classifying MRI brain scans into four categories: Glioma, Meningioma, No Tumor, and Pituitary Tumor.

The major outcomes are:

- Pituitary Tumor: Achieved 100%

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recall (400/400), showing strong identification of this class.

- No Tumor: Achieved 84.5% recall (338/400), demonstrating reliable healthy-brain classification.
- Training Performance: Reached approximately 93% training accuracy over 41 epochs with early stopping.
- Modular Prediction: The predict.py script provides reusable predictions with class-wise probability scores.
- Areas for Improvement: Glioma and Meningioma recall remained relatively low at 14.75% and 25.25%, respectively, indicating the need for further model optimization.

Key Learnings

1. Per-Class Evaluation: Accuracy alone can hide important classification failures; confusion matrices and class-wise metrics are essential.
2. Regularization: L2 weight decay, Dropout, and label smoothing helped reduce the train-validation accuracy gap.
3. Class Imbalance and Bias: Focal Loss and class-weighted training can be explored to improve difficult class predictions.
4. Training Callbacks: ModelCheckpoint, EarlyStopping, and ReduceLROnPlateau provide effective training control.
5. Dataset Organization: Correct verification of class labels and directory ordering is essential for reliable classification.
6. Clinical Considerations: Accuracy, inference speed, model size, and interpretability are important for future deployment.

Final Remarks

The project demonstrates the potential of deep learning for MRI-based brain tumor classification and provides a complete machine learning pipeline from image preprocessing to prediction and evaluation. Future improvements such as class-balanced training, transfer learning, Grad-CAM explainability, and larger datasets can enhance model reliability and support further research toward clinically validated decision-support applications.

REFERENCES

1. J. Cheng et al., "Enhanced Performance of Brain Tumor Classification via Tumor Region Augmentation and Partition," *PLOS ONE*, vol. 10, no. 10, 2015.
2. P. Afshar, A. Mohammadi, and K. N. Plataniotis, "Brain Tumor Type Classification via Capsule Networks," *Proc. IEEE ICIP*, Athens, Greece, 2018, pp. 3129–3133.
3. H. H. Sultan, N. M. Salem, and W. Al-Atabany, "Multi-Classification of Brain Tumor Images Using Deep Neural Network," *IEEE Access*, vol. 7, pp. 69215–69225, 2019.
4. S. Deepak and P. M. Ameer, "Brain Tumor Classification Using Deep CNN Features via Transfer Learning," *Computers in Biology and Medicine*, vol. 111, p. 103345, 2019.
5. Z. Hussain, F. Gimenez, D. Yi, and D. Rubin, "Differential Data Augmentation Techniques for Medical Imaging Classification Tasks," *Proc. AMIA Annual Symposium*, 2017.
6. F. Chollet, *Deep Learning with Python*, 2nd ed. Manning Publications, 2021.
7. A. Géron, *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow*, 3rd ed. O'Reilly Media, 2022.
8. TensorFlow, "tf.keras.utils.image_dataset_from_directory," TensorFlow Documentation, 2025.
9. Kaggle, "Brain Tumor MRI Dataset," 2025.
10. R. R. Selvaraju et al., "Grad-CAM: Visual Explanations from Deep Networks via Gradient-Based Localization," *Proc. IEEE ICCV*, Venice, Italy, 2017, pp. 618–626.
11. A. Işın, C. Direkoğlu, and M. Şah, "Review of

International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper

MRI-Based Brain Tumor Image Segmentation Using Deep Learning Methods," *Procedia Computer Science*, vol. 102, pp. 317–324, 2016.

12. N. J. Siddiqi and M. A. M. Khan, "A Review of Brain Tumor Classification Using Machine Learning and Deep Learning Techniques," *Medical Imaging and Computer-Aided Diagnosis*, 2020.
13. S. M. Anwar et al., "Medical Image Analysis Using Convolutional Neural Networks: A Review," *Journal of Medical Systems*, vol. 42, 2018.
14. S. Pereira, A. Pinto, V. Alves, and C. A. Silva, "Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images," *IEEE Transactions on Medical Imaging*, vol. 35, no. 5, pp. 1240–1251, 2016.
15. K. A. H. et al., "Brain Tumor Classification Using Deep Learning and Transfer Learning," *IEEE Conference Publications*, 2021.
16. M. N. H. et al., "A Deep Transfer Learning Framework for Multi-Class Brain Tumor Classification Using MRI," *IEEE Conference Publication*, 2021.
17. S. A. Khan et al., "Brain Tumor/Mass Classification Framework Using Magnetic-Resonance-Imaging-Based Transfer Deep-Learning Model," *Computers in Biology and Medicine*, 2022.
18. M. R. N. et al., "Recent Advances in Classification of Brain Tumor from MR Images: State of the Art Review from 2017 to 2021," 2022.
19. "Convolutional Neural Network Techniques for Brain Tumor Classification (2015–2022): Review, Challenges, and Future Perspectives," *Journal of Medical Internet Research*, 2022.
20. "Automated Classification of Brain Tumors from Magnetic Resonance Imaging Using Deep Learning," *Medical Engineering & Physics*, 2023.
21. "Abnormal Brain Tumors Classification Using ResNet50 and Its Comprehensive Evaluation," *IEEE Access*, vol. 12, pp. 78843–78853, 2024.
22. "Ensemble Deep Learning Models for Enhanced Brain Tumor Classification by Leveraging ResNet50 and EfficientNet-B7 on High-Resolution MRI Images," *IEEE Access*, vol. 12, pp. 178623–178641, 2024.
23. R. Disci, F. Gurcan, and A. Soylu, "Advanced Brain Tumor Classification in MR Images Using Transfer Learning and Pre-Trained Deep CNN Models," *Cancers*, vol. 17, no. 1, p. 121, 2025.
24. "Hybrid CNN-Based Transfer Learning Enhances Brain Tumor Classification on MRI Images," *IEEE Access*, vol. 13, pp. 116654–116668, 2025.
25. "Lightweight Transfer Learning Models for Multi-Class Brain Tumor Classification: Glioma, Meningioma, Pituitary Tumors, and No Tumor MRI Screening," 2025
26. F. J. Dorfner, J. B. Patel, J. Kalpathy-Cramer, E. R. Gerstner, and C. P. Bridge, "A review of deep learning for brain tumor analysis in MRI," *npj Precision Oncology*, vol. 9, no. 1, p. 2, 2025.
27. S. Bouhafra and H. El Bahi, "Deep Learning Approaches for Brain Tumor Detection and Classification Using MRI Images (2020 to 2024): A Systematic Review," *Journal of Imaging Informatics in Medicine*, vol. 38, no. 3, pp. 1403–1433, 2025.
28. Y. Wong, E. L. M. Su, C. F. Yeong, W. Holderbaum, and C. Yang, "Brain tumor classification using MRI images and deep learning techniques," *PLOS ONE*, vol. 20, no. 5, e0322624, 2025.
29. R. Missaoui, W. Hechkel, W. Saadaoui, A. Helali, and M. Leo, "Advanced Deep Learning and Machine Learning Techniques for MRI Brain Tumor Analysis: A Review," *Sensors*, vol. 25, no. 9, p. 2746, 2025.
30. N.-H. Lu, Y.-H. Huang, K.-Y. Liu, and T.-B. Chen, "Deep learning-driven brain tumor classification and segmentation using non-contrast MRI," *Scientific Reports*, vol. 15, p. 27831, 2025.