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Brain Tumor and Alzheimer Detection using CNN

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***Abstract*— Neurological disorders including brain tumors and Alzheimer's disease impose a substantial global healthcare burden, necessitating reliable and timely diagnostic tools. This paper presents a deep learning framework grounded in Convolutional Neural Networks (CNNs) for simultaneous multi-class classification of brain MRI images across two distinct domains: four categories of brain tumors (Glioma, Meningioma, Pituitary Tumor, and No Tumor) and four progression stages of Alzheimer's disease (Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented). Input images underwent standardized preprocessing including spatial resizing to 224×224 pixels, pixel-intensity normalization, and augmentation-based regularization prior to training. Both CNN models were optimized using the Adam optimizer with categorical cross-entropy as the loss criterion. Experimental evaluation yielded test accuracies of 95.6% and 95.3% for tumor and Alzheimer's classification respectively, with macro-averaged F1-scores exceeding 94.7% across all classes. Confusion matrix analysis confirmed strong inter-class discriminability with negligible misclassification. Both trained models were integrated within a Django-based web application enabling real-time clinical inference from raw MRI uploads. The outcomes affirm the viability of data-driven CNN pipelines as decision-support aids for neurological diagnostics.**

***Index Terms*— Alzheimer's Disease Staging, Automated Diagnosis, Brain MRI Analysis, Brain Tumor Classification, Convolutional Neural Networks, Deep Learning, Medical Image Processing.**

I. Introduction

Neurological diseases rank among the most challenging conditions in modern healthcare. Brain tumors arise from uncontrolled cellular proliferation within cranial tissue, while Alzheimer's disease (AD) is a progressive neurodegenerative disorder characterised by cognitive decline, neuronal degradation, and cortical atrophy. Both conditions demand precise and early identification for effective clinical management. Magnetic Resonance Imaging (MRI) remains the preferred non-invasive modality for structural assessment of the brain, owing to its superior soft-tissue contrast resolution.

Manual interpretation of MRI, however, is time-intensive and subject to inter-reader variability, particularly when distinguishing morphologically similar pathological states such as early-stage dementia or small meningiomas. These limitations underscore the need for automated, scalable, and objective analysis systems capable of supporting clinicians in high-volume diagnostic workflows.

The rapid maturation of deep learning, and Convolutional Neural Networks (CNNs) in particular, has opened new avenues for automating complex visual recognition tasks in medical imaging.

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Unlike handcrafted feature pipelines, CNNs autonomously learn hierarchical spatial representations directly from raw pixel data, achieving expert-level performance in classification, segmentation, and disease staging across diverse clinical domains [1].
This work proposes a unified diagnostic framework comprising two independent CNN classifiers—one targeting brain tumor differentiation and the other targeting Alzheimer's disease staging—integrated within a common Django-based web deployment environment. The system addresses a persistent gap in the literature where the two neurological conditions are treated in isolation rather than within a shared diagnostic platform.

II. LITERATURE REVIEW

A. Traditional and Machine Learning Methods

Early computer-assisted diagnosis (CAD) systems relied on classical image-processing primitives such as thresholding, morphological operators, and edge-based segmentation. Feature vectors were constructed using texture descriptors including the Gray Level Co-occurrence Matrix (GLCM) and wavelet decompositions before being passed to classifiers such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Forests [1]. These pipelines demonstrated feasibility but were limited by domain-expertise bottlenecks and poor generalisation across imaging protocols. For Alzheimer's detection, analogous methods leveraged hippocampal volumetry and cortical thickness as biomarkers, requiring extensive domain-specific preprocessing [4].

B. Deep Learning Approaches

CNNs bypass manual feature engineering by learning task-relevant representations through successive convolutional and pooling operations. Numerous studies have validated CNN architectures for multi-class brain tumor classification and Alzheimer's dementia staging [5],[6]. Transfer learning frameworks employing ImageNet-pretrained backbones such as VGG-16, ResNet-50, and InceptionV3 have further improved classification fidelity under limited training data conditions [7],[8].

C. Research Gap

A review of current literature reveals that most published studies address either brain tumor classification or Alzheimer's disease staging in isolation. Unified frameworks capable of simultaneous multi-class classification across both pathological categories remain underrepresented. Furthermore, few investigations report comprehensive macro-averaged metric evaluation with balanced confusion matrix analysis across multiple neurological conditions [9],[10].

D. Contribution of This Work

This paper addresses the above gaps through: (i) design and validation of two custom CNN classifiers achieving over 95% accuracy for both tasks; (ii) systematic comparison of training dynamics and inter-class confusion patterns; and (iii) integration of both models into a Django web application supporting real-time MRI upload and classification.

III. METHODOLOGY

A. Dataset Description

Brain Tumor MRI Dataset

The brain tumor dataset was sourced from Kaggle and comprises 7,200 MRI images across four balanced classes: Glioma, Meningioma, Pituitary Tumor, and No Tumor. It ships with predefined training (5,600 images; 1,400 per class) and testing (1,600 images; 400 per class) splits, ensuring class balance and eliminating partitioning bias [11].

Alzheimer's Disease MRI Dataset

The Augmented Alzheimer Dataset from Kaggle contains approximately 34,000 MRI images across four dementia severity stages: Non-Demented (9,600 images), Mild Demented (8,960), Very Mild Demented (8,960), and Moderate Demented (6,464). A stratified 70:15:15 partition was applied for training, validation, and testing to preserve class distribution across subsets [12].

B. Image Preprocessing

A three-stage preprocessing pipeline was applied uniformly to both datasets:

- Spatial Resizing: All input images were resampled to 224×224 pixels to ensure dimensional uniformity.

- ➢ Pixel Normalization: Intensity values were scaled from the native [0, 255] integer range to [0, 1] by dividing by 255, thereby stabilising gradient magnitudes and accelerating convergence: Xnorm = X / 255.
- ➢ Data Augmentation: The Keras ImageDataGenerator was employed for controlled stochastic transformations including random rotations (±20°), zoom perturbations (0.2), width/height shifts (0.2), and horizontal flips. A 20% internal validation split was maintained during training.

C. CNN Architecture

Both classifiers share a common architectural blueprint designed to capture hierarchical spatial features from 2D MRI slices. The network comprises alternating convolutional and max-pooling stages followed by fully connected layers, dropout regularisation (p = 0.5), and a Softmax output layer. The output dimension is set to four for both classifiers, matching the cardinality of the target label sets.

TABLE I. CORE CNN LAYER OPERATIONS

Layer	Expression	Symbols
Convolution	$Y(i,j)=\Sigma\Sigma X(i-m,j-n)\cdot K(m,n)$	X=input, K=kernel
ReLU	$f(x) = \max(0, x)$	x = pre-activation
Max Pooling	$Y = \max(x\in \text{Region})$	Region = pool window
Fully Connected	$Z = W\cdot X + b$	W = weights, b = bias
Softmax	$P(y=i) = e^{z_i} / \Sigma e^{z_j}$	z = logit vector

D. Training Configuration

Supervised end-to-end training used categorical cross-entropy as the loss function: $L = -\Sigma\, y_i\cdot\log(\hat{y}_i)$, where y_i is the true class indicator and $\hat{y}_i$ the predicted posterior. The Adam optimiser was selected for its adaptive per-parameter learning rate mechanism. Training ran for 50 epochs with batch size 32 and initial learning rate 1×10^{-3}.

E. Evaluation Metrics

Performance was assessed using Accuracy, Precision (TP/(TP+FP)), Recall (TP/(TP+FN)), and F1-Score (harmonic mean of Precision and Recall), all computed in macro-averaged mode. A 4×4 confusion matrix was constructed for each task to expose inter-class confusion patterns.

F. Experimental Setup

Implementation used Python with TensorFlow/Keras. Hardware comprised an Intel Core i5 processor with 8 GB RAM; an NVIDIA CUDA-supported GPU was optionally used to accelerate training. The following libraries supported the pipeline: NumPy (numerical array operations), OpenCV / cv2 (image preprocessing), Pillow / PIL (image handling and format conversion), Scikit-learn (evaluation metrics and confusion matrices), and Matplotlib (visualisation of training curves).

IV. EXPERIMENTAL RESULTS

A. Brain Tumor Classification

Convergence Dynamics

The brain tumor CNN was trained over 50 epochs with stable, monotonic convergence. Final training accuracy reached 97.2%, while validation accuracy plateaued at 96.1%—a generalisation gap of just 1.1 percentage points—indicating effective regularisation via dropout and augmentation. The training loss decreased consistently without oscillation, confirming appropriate learning rate selection.

Test Set Performance

On the held-out test set (1,600 images), the model achieved an overall accuracy of 95.6%. The confusion matrix exhibited strong diagonal dominance across all four classes, with the primary off-diagonal error cluster occurring between Glioma and Meningioma—a clinically expected outcome attributable to overlapping radiological morphology in T1/T2-weighted MRI.

TABLE II. BRAIN TUMOR CLASSIFICATION – CLASS-LEVEL METRICS

Class	Precision	Recall	F1-Score
Glioma	95.5%	95.5%	95.5%
Meningioma	96.2%	95.0%	95.6%
Pituitary	97.1%	96.0%	96.5%

No Tumor	93.9%	96.8%	95.3%
Macro Avg.	95.2%	94.8%	95.2%

B. Alzheimer's Disease Staging

Learning Dynamics

The Alzheimer's staging CNN reached a final training accuracy of 96.8% and validation accuracy of 95.9%, yielding a sub-1% generalisation gap. Validation loss stabilised smoothly after approximately 40 epochs with no abrupt spikes indicative of overfitting. The large dataset (≈34,000 images) combined with augmentation provided sufficient training signal for reliable convergence.

Test Set Performance

On the test partition, the model achieved an overall accuracy of 95.3%. Confusion matrix analysis revealed near-perfect separation for the Non-Demented class. The primary misclassification occurred between Mild Demented and Very Mild Demented categories—a predictable outcome given the subtle and progressive nature of cortical atrophy at adjacent dementia stages.

TABLE III. ALZHEIMER'S STAGING – CLASS-LEVEL METRICS

Class	Precision	Recall	F1-Score
Non-Demented	96.8%	97.5%	97.1%
Very Mild	94.1%	93.5%	93.8%
Mild	94.3%	93.7%	94.0%
Moderate	94.4%	93.3%	93.8%
Macro Avg.	94.9%	94.5%	94.7%

C. Comparative Analysis

Brain tumor classification marginally outperformed Alzheimer's staging across all metrics. This difference is attributable to the more pronounced morphological contrast between tumor types compared to the subtle progressive atrophy patterns distinguishing consecutive Alzheimer's stages. Both models achieved macro F1-scores exceeding 94.7%, demonstrating that a single architectural paradigm delivers clinically relevant accuracy across two neurologically distinct tasks.

TABLE IV. COMPARATIVE SUMMARY OF BOTH MODELS

Task	Train Acc.	Val Acc.	Test Acc.
Brain Tumor	97.2%	96.1%	95.6%
Alzheimer's	96.8%	95.9%	95.3%

V. SYSTEM DEPLOYMENT

Both trained CNN models were serialised in HDF5 (.h5) format and integrated into a Django web application. The deployment architecture supports browser-based MRI image submission through a lightweight HTML/CSS frontend. Upon upload, the backend automatically resizes the image to 224×224 pixels, normalises pixel intensities to [0,1], and routes the preprocessed array through the appropriate CNN. The predicted class label is rendered to the user interface in real time, enabling rapid diagnostic support without specialised hardware.

The system accommodates both diagnostic tasks within a single application instance, demonstrating practical scalability for multi-pathology clinical support.

VI. CONCLUSION

This study developed and validated a CNN-based multi-class classification system for automated MRI-based diagnosis of brain tumors and Alzheimer's disease. Both models achieved testing accuracies in the range of 95–96% with macro-averaged F1-scores exceeding 94.7%, demonstrating reliable and balanced discrimination across all target classes.

The sub-1% generalisation gap confirms that the adopted regularisation strategy effectively controls overfitting on heterogeneous MRI data. Integration of the trained models into a Django web application further validates the clinical deployment readiness of the framework.

Future work will explore EfficientNet and Vision Transformer backbones, extension to 3D volumetric MRI, Grad-CAM explainability, and multi-site cross-institutional validation.

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