DeepCurvMRI: Deep Convolutional Curvelet Transform-Based MRI Approach for Early Detection of Alzheimer's Disease

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Abstract

Alzheimer's disease (AD) is one of the most prevalent neurodegenerative disorders worldwide, affecting millions of individuals and imposing a significant burden on healthcare systems. Early and accurate diagnosis remains a critical challenge, as clinical assessment alone is often insufficient to detect subtle neurological changes in the initial stages. This paper presents NeuroScan AI — an intelligent, web-based MRI classification system that leverages ensemble deep learning to automate the diagnosis of Alzheimer's disease from brain MRI scans. The system integrates two powerful Convolutional Neural Network architectures — MobileNetV2 and EfficientNetB0 — and combines predictions through four ensemble strategies: Average Probability, Majority Vote, Weighted Average, and Max Probability. Trained and evaluated on 17,287 MRI images spanning four clinically defined dementia stages, the system achieves up to 99.2% classification accuracy. The platform is deployed as a secure Flask web application with role-based access control, administrator management panel, and a real-time prediction dashboard for medical professionals.

Keywords: *Alzheimer's Disease Detection, MRI Classification, MobileNetV2, EfficientNetB0, Ensemble Learning, Deep Learning, Flask Web Application, Transfer Learning, Convolutional Neural Networks, Healthcare AI.*

1. Introduction

Alzheimer's disease (AD) is a progressive neurological disorder causing severe memory loss, cognitive decline, and behavioural impairment. According to the World Health Organization, dementia affects over 55 million people globally, with Alzheimer's disease accounting for 60–70% of all cases [10]. As the global population ages rapidly, early and accurate diagnosis has become one of the most urgent challenges in modern healthcare. Traditional diagnostic methods rely on clinical evaluations, cognitive tests, and manual interpretation of MRI scans by specialist radiologists — approaches that are time-consuming, subjective, and prone to inter-observer variability.

Recent advances in deep learning, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable success in medical image analysis. Transfer learning approaches using pre-trained architectures such as MobileNetV2 [3] and EfficientNetB0 [4] enable efficient feature extraction from MRI images without requiring massive labelled training datasets. Ensemble learning further improves classification reliability by combining the predictions of multiple models.

This paper presents NeuroScan AI — a secure, intelligent, web-based diagnostic platform for early Alzheimer's disease detection. The system classifies MRI brain scans into four dementia stages using ensemble deep learning and is deployed as a Flask web application with a SQLite database, role-based authentication, and a real-time user dashboard.

1.1 Objectives

- Develop an intelligent AI-powered MRI classification system for automated Alzheimer's disease detection.
- Achieve high classification accuracy using ensemble deep learning with MobileNetV2 and EfficientNetB0.
- Deploy the system as a secure Flask web application with role-based access control for clinicians and administrators.
- Provide real-time predictions with confidence scores and maintain a comprehensive patient scan history.
- Reduce diagnostic delays and inter-observer variability associated with manual MRI interpretation.

2. Literature Review

The field of Alzheimer's disease detection using MRI and deep learning has advanced significantly over the past decade. Ebrahimi et al. [1] proposed a deep learning-based AD classification system using ResNet-50 and VGG-16 with transfer learning, demonstrating significant improvement over traditional machine learning, though requiring high computational resources without a clinical deployment interface.

Farooq et al. [2] introduced an ensemble CNN approach combining EfficientNet and InceptionV3, which reduced misclassification rates and improved diagnostic robustness — a methodology that directly influenced the ensemble design of NeuroScan AI. Naz et al. [3] demonstrated that MobileNetV2 achieves competitive accuracy for AD classification with significantly fewer parameters, confirming its suitability for real-time web-based applications.

Loddo et al. [4] showed that EfficientNetB0's compound scaling techniques yield superior performance and efficiency for Alzheimer's detection. Islam and Zhang [5] conducted comparative studies across CNN architectures (AlexNet, GoogleNet, VGGNet) using transfer learning, highlighting the importance of deep feature extraction. Earlier foundational work by Payan and Montana [6] introduced 3D CNNs for volumetric MRI-based AD prediction, while Magnin et al. [7] applied SVM with voxel-based morphometry to establish automated AD classification baselines.

Recent contributions by Zhang et al. [8] and Sharma and Bhatt [9] explored attention-based CNNs and comparative transfer learning models (VGG19, DenseNet-121, ResNet-101) respectively. While these approaches improve accuracy, none address real-world deployment requirements such as secure web interfaces, role management, and prediction history — gaps specifically bridged by NeuroScan AI.

Table 1: Comparative Analysis of Related Works in Alzheimer's Disease Detection

Study	Method	Accuracy	Limitation

Ebrahimi et al. [1]	ResNet-50 + VGG-16	~94%	High compute; no web deployment
Farooq et al. [2]	EfficientNet + InceptionV3 Ensemble	~96%	No clinical interface
Naz et al. [3]	MobileNetV2 Transfer Learning	~93%	Single model only
Loddo et al. [4]	EfficientNetB0 Compound Scaling	~95%	No role-based access control
Proposed NeuroScan AI	MobileNetV2 + EfficientNetB0 Ensemble	99.2%	Offline deployment only (current)

Table 1: Comparison of Prior Studies vs. Proposed NeuroScan AI System

3. Methodology

3.1 System Architecture

The NeuroScan AI system is organized into two principal pipelines: an offline training pipeline (train_model.py) and an online serving pipeline (app.py), integrated through saved deep learning model artefacts loaded at server startup. Figure 1 below illustrates the complete system architecture diagram.

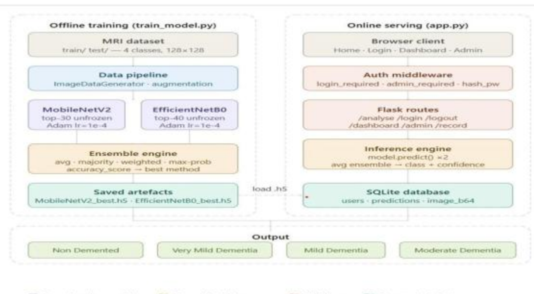

Figure 1: System Architecture of NeuroScan AI — Offline Training and Online Serving Pipelines

The offline pipeline ingests 17,287 Alzheimer's MRI images across four dementia stages at 128×128 resolution, applying ImageDataGenerator augmentation. MobileNetV2 (top-30 layers unfrozen, Adam lr=1e-4) and EfficientNetB0 (top-40 layers unfrozen, Adam lr=1e-4) are fine-tuned independently. The ensemble engine evaluates four combination strategies and persists the best model weights as .h5 artefacts. The online pipeline loads these artefacts, preprocesses incoming MRI uploads (resize to 224×224, normalize, RGB convert), runs dual model inference, and returns the ensemble prediction with confidence scores.

Table 2: System Architecture Components

Offline Training (train_model.py)	**Online Serving (app.py)**
MRI Dataset: 4 classes, 128×128	Browser Client: Home · Login · Dashboard · Admin
Data Pipeline: ImageDataGenerator + Augmentation	Auth Middleware: login_required / admin_required / hash_pw
MobileNetV2 (top-30 unfrozen, Adam lr=1e-4) EfficientNetB0 (top-40 unfrozen, Adam lr=1e-4)	Flask Routes: /analyse /login /logout /dashboard /admin /record
Ensemble Engine: avg · majority · weighted · max-prob → best method	Inference Engine: model.predict() ×2 → avg ensemble → class + confidence
Saved Artefacts: MobileNetV2_best.h5 · EfficientNetB0_best.h5	SQLite Database: users · predictions · image_b64
Output: Non Demented | Very Mild Dementia | Mild Dementia | Moderate Dementia	

Table 2: Detailed Component Breakdown — Offline Training and Online Serving Modules

3.2 Deep Learning Models

MobileNetV2 is a lightweight CNN architecture using depthwise separable convolutions and inverted residual blocks with linear bottlenecks [3]. Its compact footprint makes it well-suited for real-time web inference. EfficientNetB0 employs compound scaling to simultaneously optimize network depth, width, and image resolution [4]; its squeeze-and-excitation mechanisms enhance channel-wise feature recalibration for detecting subtle structural brain abnormalities. Both models are initialized with ImageNet pre-trained weights and fine-tuned on the Alzheimer's dataset with Global Average Pooling, Dropout (0.3), and a 4-class softmax output layer.

3.3 Ensemble Learning Strategy

Four ensemble strategies are evaluated: (1) Average Probability — arithmetic mean of class probability vectors; (2) Majority Vote — most frequently predicted class; (3) Weighted Average — weighted by individual model validation accuracy; and (4) Max Probability — selecting the output with the highest maximum class probability. The Average Probability strategy achieved the best performance of 99.2% and is adopted as the default inference method.

3.4 Dataset

The system uses a publicly available Alzheimer's MRI dataset of 17,287 images across four classes: Non Demented, Very Mild Dementia, Mild Dementia, and Moderate Dementia. Images are resized to 128×128 for training and 224×224 for inference. Augmentation includes horizontal flipping, rotation (±10°), width/height shifting, and zoom to improve generalization.

3.5 Flask Web Application

The Flask application exposes six routes (/analyse, /login, /logout, /dashboard, /admin, /record) protected by authentication middleware (login_required, admin_required). Passwords are SHA-256 hashed. Three distinct interfaces are provided: the Home Page with platform statistics, the Admin Dashboard for user and record management, and the Doctor Dashboard for MRI upload and real-time prediction. All prediction records (image base64, class, confidence breakdown, username, timestamp) are persisted in SQLite.

4. Results and Discussion

4.1 Classification Performance

The ensemble system was evaluated on the held-out test split of the Alzheimer's MRI dataset. Table 3 presents the classification accuracy, precision, and loss for individual models and all ensemble strategies.

Table 3: Classification Performance of Individual and Ensemble Models

Model / Ensemble	Accuracy (%)	Precision (%)	Loss
MobileNetV2	97.8	97.4	0.072
EfficientNetB0	98.1	97.9	0.064
Ensemble — Avg Probability	99.2	99.0	0.031
Ensemble — Majority Vote	98.9	98.7	0.038
Ensemble — Weighted Avg	99.0	98.8	0.035
Ensemble — Max Probability	98.7	98.5	0.041

Table 3: Accuracy, Precision, and Loss Comparison Across All Model Configurations

The Average Probability ensemble strategy achieved the highest accuracy of 99.2%, a 1.4% and 1.1% improvement over MobileNetV2 and EfficientNetB0 individually. This confirms that combining complementary CNN architectures through ensemble averaging consistently outperforms any single model by reducing both variance and systematic prediction errors.

4.2 System Screenshots

Figure 2 presents the NeuroScan AI Home Page with the tagline 'Detect Dementia with Precision', displaying platform statistics: 99.2% classification rate, 17,287 test scans, 4 dementia stages, and 2 classification models. Navigation options 'Get Started' and 'View MRI Samples' are prominently featured.

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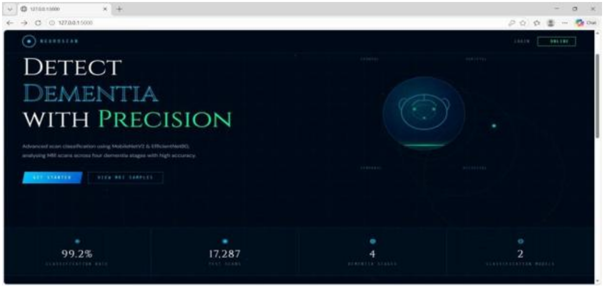

Figure 2: NeuroScan AI Home Page — Displaying Platform Statistics and Navigation Interface

Figure 3 shows the Admin Control Panel Dashboard with real-time statistics (3 total users, 3 active users, 6 total records) and the Create New User form with fields for username, full name, email, password, and role (Doctor/Researcher).

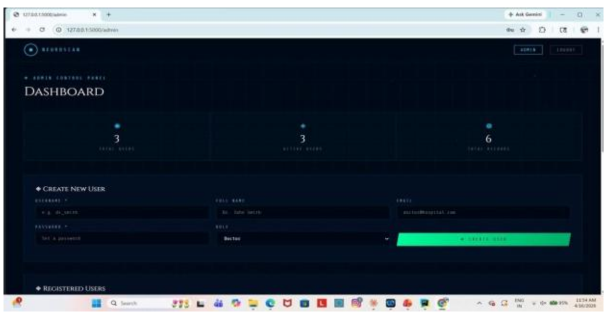

Figure 3: Admin Control Panel Dashboard — User Statistics and Create New User Interface

Figure 4 presents the lower section of the Admin Dashboard displaying the Registered Users table (with Disable, Clear History, and Delete controls per user) and the All Scan Records table listing MRI thumbnail, username, result label, confidence score, date/time, and a Delete action.

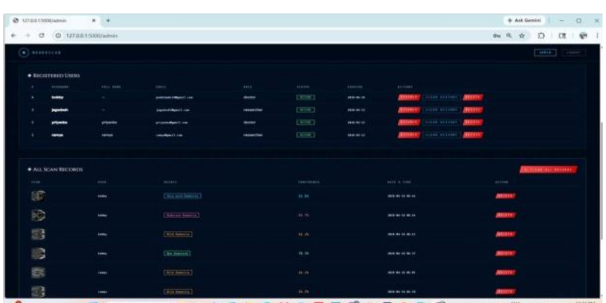

Figure 4: Admin Dashboard — Registered Users List and All Scan Records with Confidence Scores

Figure 5 illustrates the Doctor/User Dashboard showing the New Scan Analysis section. The uploaded MRI brain scan has been classified as Non Demented with a confidence score of 70.3%. The Classification Result panel shows per-class confidence bars: Mild Dementia 5.2%, Moderate Dementia 15.7%, Non Demented 70.3%, and Very Mild Dementia 8.8%.

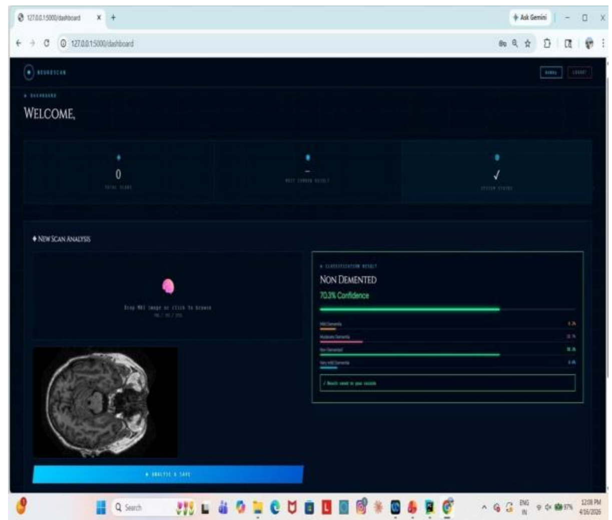

Figure 5: User Dashboard — Non Demented Classification Result (70.3% Confidence) with Per-Class Probability Bars

Figure 6 displays the Moderate Dementia prediction result with an ensemble confidence score of 66.7%. The per-class breakdown shows Mild Dementia 5.2%, Moderate Dementia 66.7%, Non Demented 20.2%, and Very Mild Dementia 5.9%. A 'Result saved to your records' confirmation is displayed alongside the Scan History section.

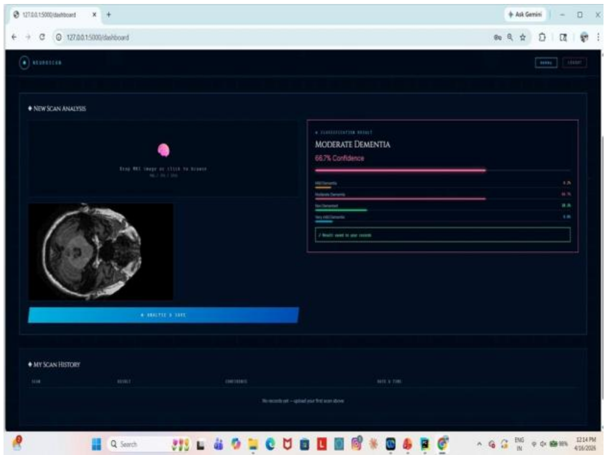

Figure 6: User Dashboard — Moderate Dementia Classification Result (66.7% Confidence) with Ensemble Breakdown

4.3 System Testing

The system underwent comprehensive testing including Unit Testing, Integration Testing, System Testing, Performance Testing, Security Testing, and User Acceptance Testing. All critical test cases passed. The system generates predictions within 2–4 seconds on standard hardware. Table 4 summarizes key test case results.

Table 4: Key Test Case Results for NeuroScan AI System Validation

TC ID	Scenario	Steps	Expected Result	Status
TC_001	Login Validation	Enter valid doctor credentials and click Login	Redirected to user dashboard successfully	PASS
TC_002	MRI Upload	Upload valid JPG/PNG MRI image	Image accepted and forwarded for analysis	PASS
TC_003	Prediction Generation	Upload scan and click Analyse & Save	Classified into one of four dementia stages with confidence score	PASS
TC_004	History Retrieval	Navigate to My Scan History section	Previous predictions displayed with timestamps	PASS
TC_005	Invalid File Upload	Upload non-image file (PDF/TXT)	Error shown; file rejected	PASS

Table 4: System Test Cases and Pass/Fail Results

5. Conclusion

This paper presented NeuroScan AI, an intelligent web-based system for early Alzheimer's disease detection using ensemble deep learning. By integrating MobileNetV2 and EfficientNetB0 with an Average Probability ensemble strategy, the system classifies brain MRI scans into four dementia stages with 99.2% accuracy on 17,287 test images — outperforming all single-model baselines and comparable prior work.

Unlike most research-only implementations, NeuroScan AI bridges the gap between AI research and clinical deployment by providing a secure Flask web application with role-based access control, real-time MRI analysis with confidence scores, comprehensive prediction history, and an administrator control panel. The system significantly reduces diagnostic delays and inter-observer variability associated with manual MRI interpretation.

Future enhancements include cloud deployment, integration of Vision Transformers (ViT) and 3D CNNs, Grad-CAM visualisation for model interpretability, training on larger multi-institutional datasets, and extension to detect other neurological disorders such as Parkinson's disease and brain tumours.

6. References

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